Flexible Gating of Contextual Influences in Natural Vision

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Oct 2015

Contextual influences

- Perceptual illusions: “no man is an island..”

Review paper on context:
Schwartz, Hsu, Dayan, Nature Reviews Neuroscience 2007

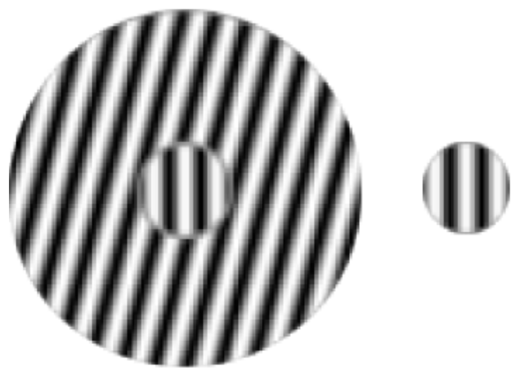
Contextual influences

- Perceptual illusions: “no man is an island..”

Review paper on context:
Schwartz, Hsu, Dayan, Nature Reviews Neuroscience 2007

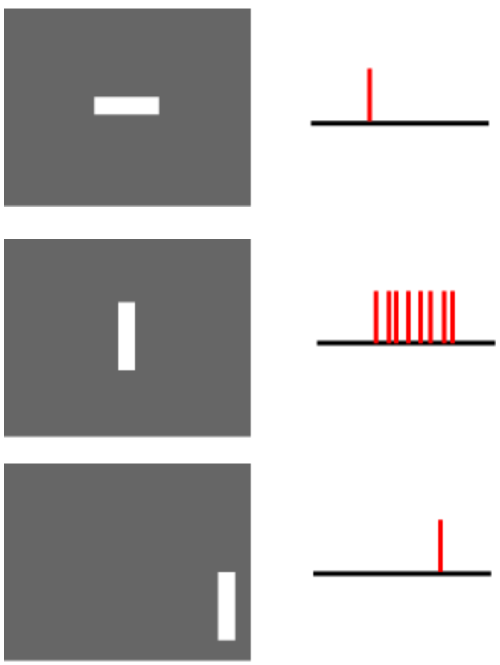
Contextual influences

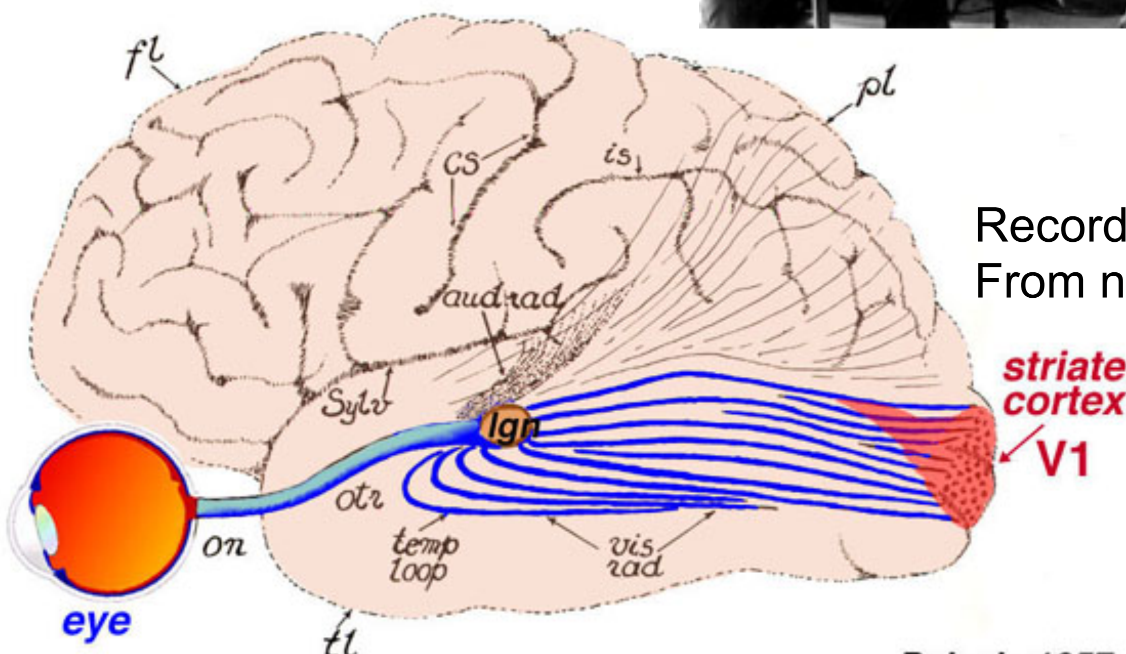
- Perceptual illusions



What about neurons?

- Cortical neural processing



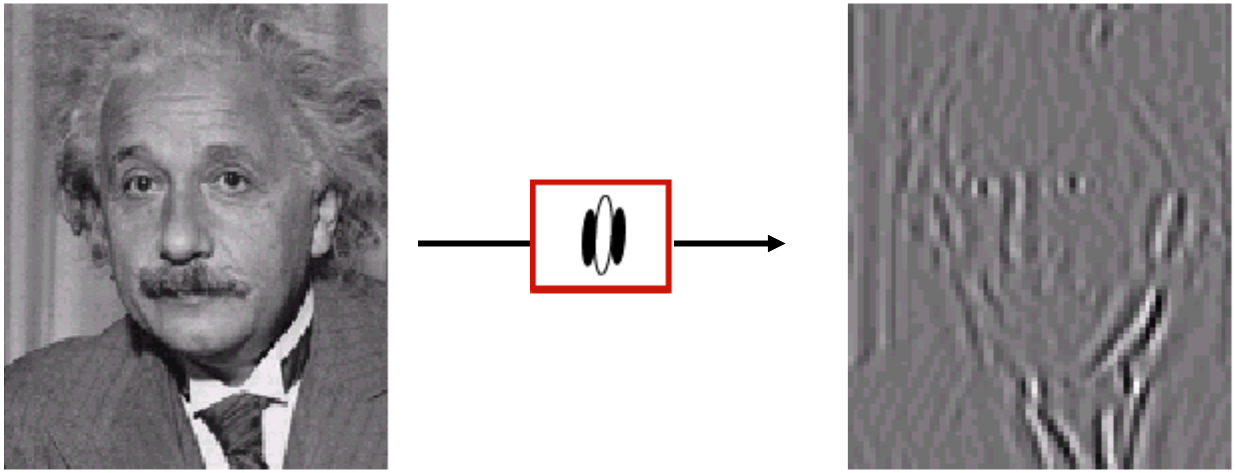


Record
From neuron

Polyak, 1957

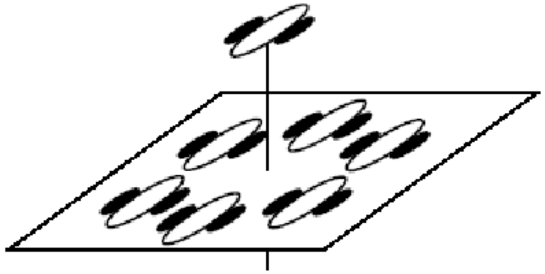
What about neurons?

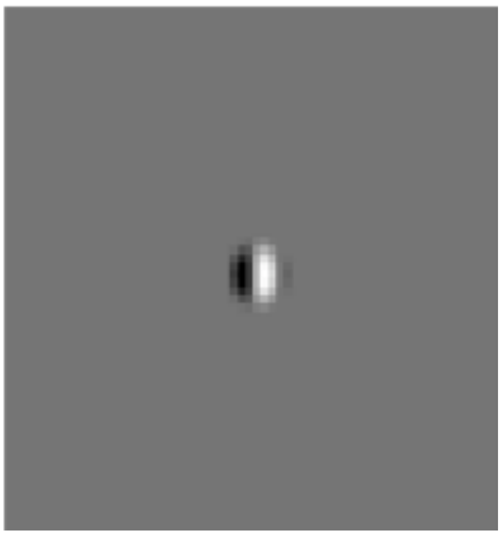
- Computer science / Engineering: visual receptive field or filter

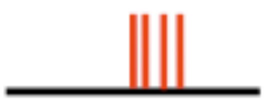


Contextual influences

- Cortical visual neurons (V1)







??

Motivation

- Spatial context plays critical role in object *grouping* and recognition, and in *segmentation*. It is key to everyday behavior; deficits have been implicated in neurological and developmental disorders and aging

- Range of existing experimental data on spatial context (neural; perceptual). Lacking principled explanation

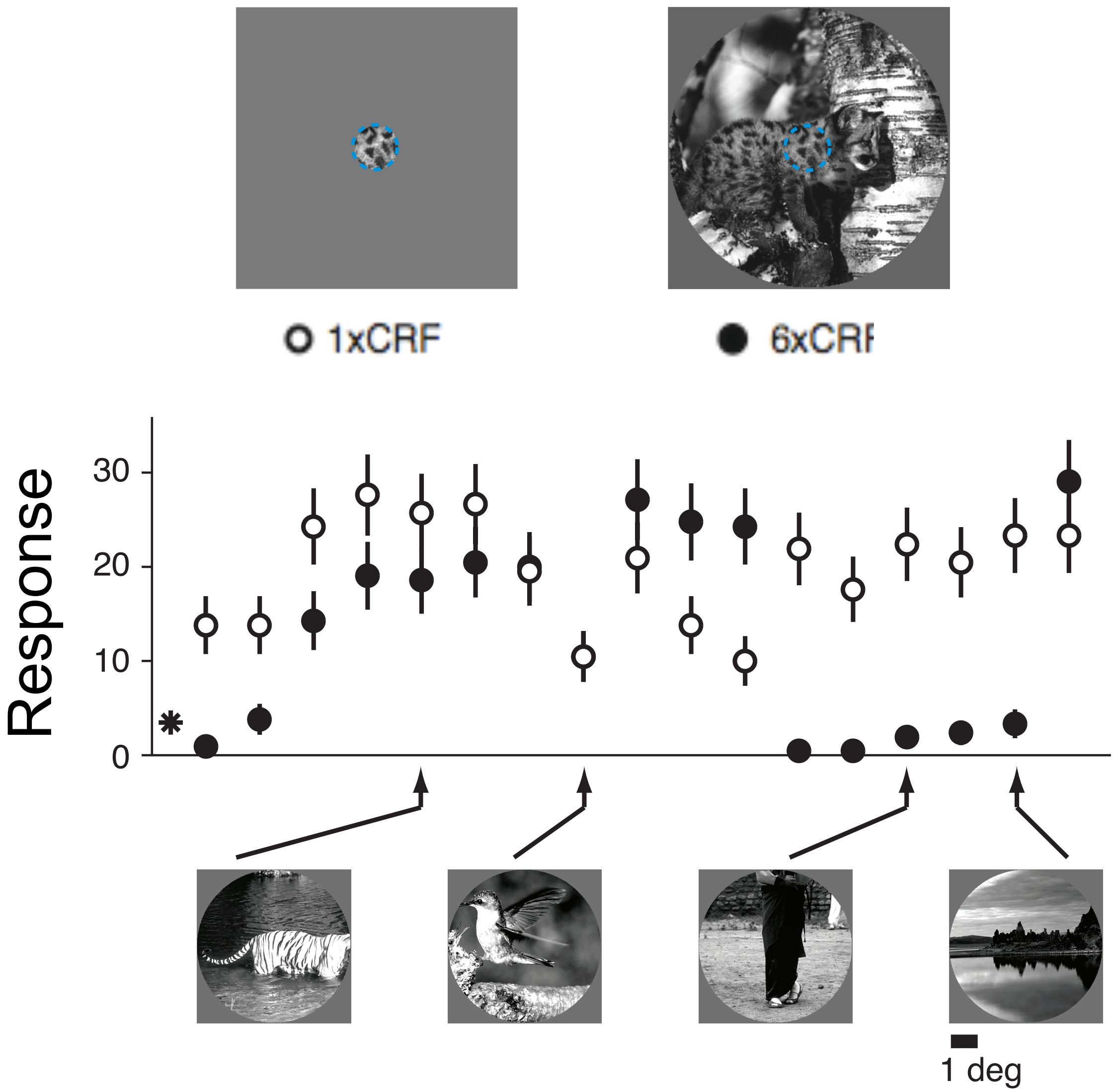
- Poor understanding for how we (and our cortical neurons) process complex, natural images

Outline

- Experimental data on cortical responses to natural images
- Computational neural model that captures contextual regularities in natural images
- Interplay of modeling with biological neural and psychology data (focus on natural images data)

Cortical Neurons

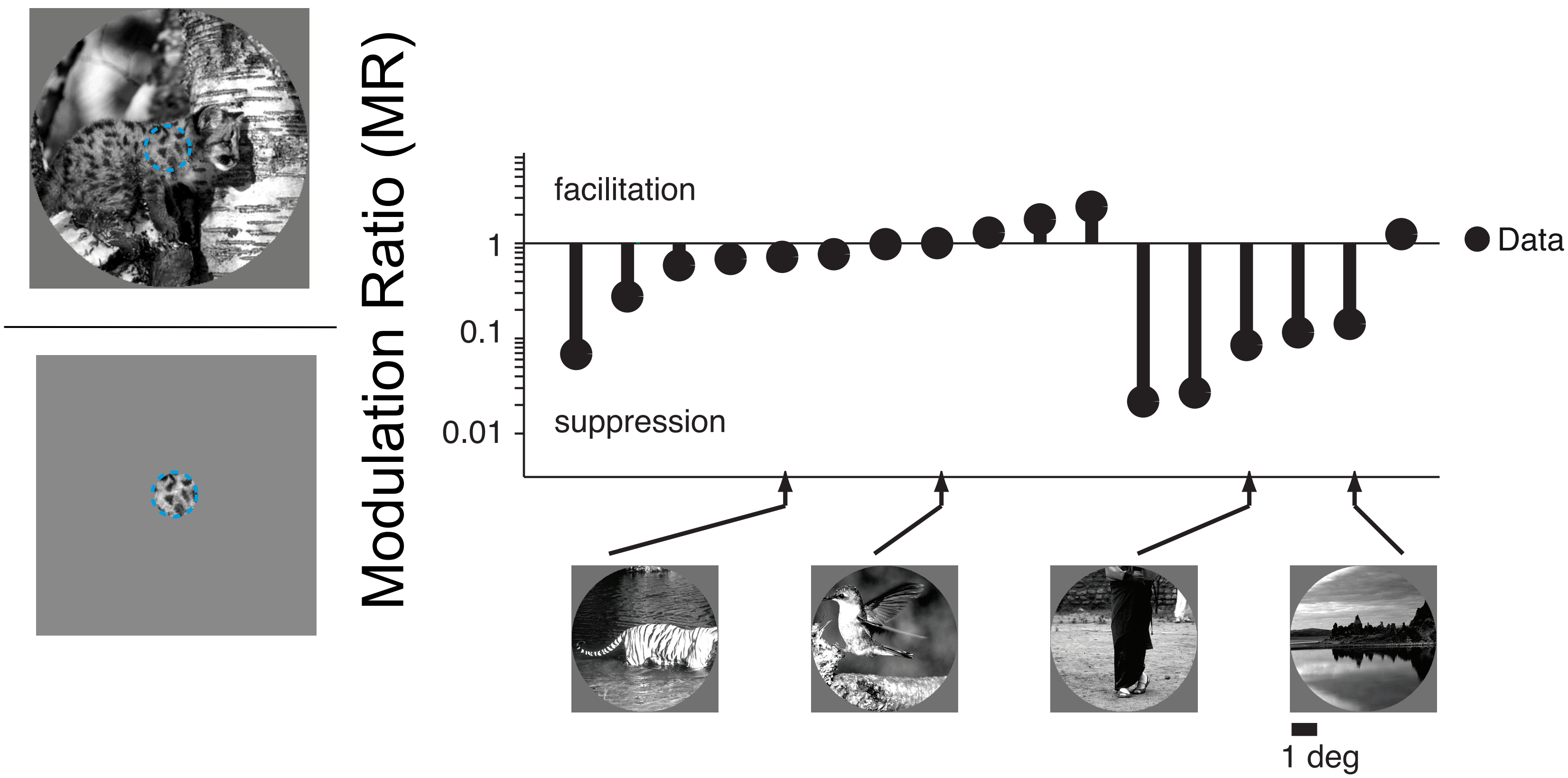
- Spatial context and natural scenes



Data: Adam Kohn lab (Coen-Cagli, Kohn, Schwartz, 2015; in press)

Cortical Neurons

- Spatial context and natural scenes



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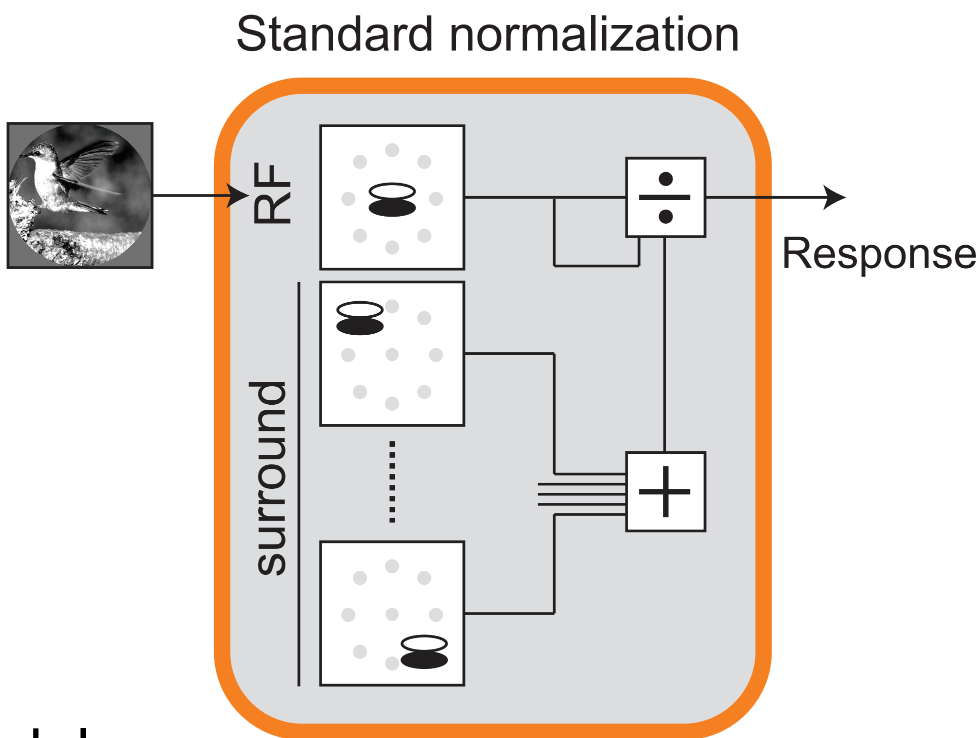
Cortical Neurons

- Spatial context and natural scenes

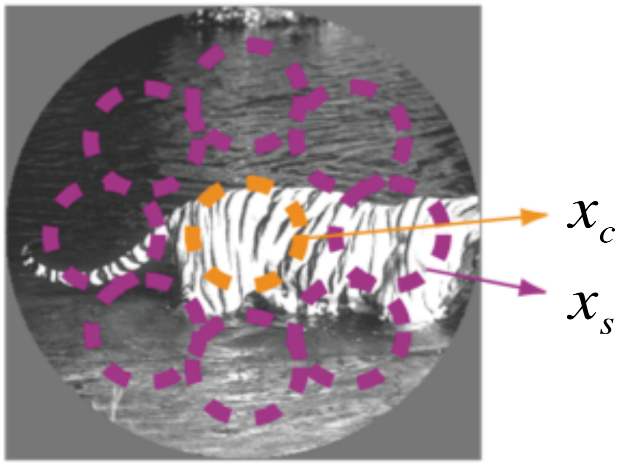
Can we capture data with canonical divisive normalization? (descriptive model)

Divisive normalization



- Descriptive model
- Canonical computation (Carandini, Heeger, Nature Reviews Neuro, 2012)
- Has been applied to visual cortex, as well as other systems and modalities, multimodal processing, value encoding, etc

Cortical Neurons

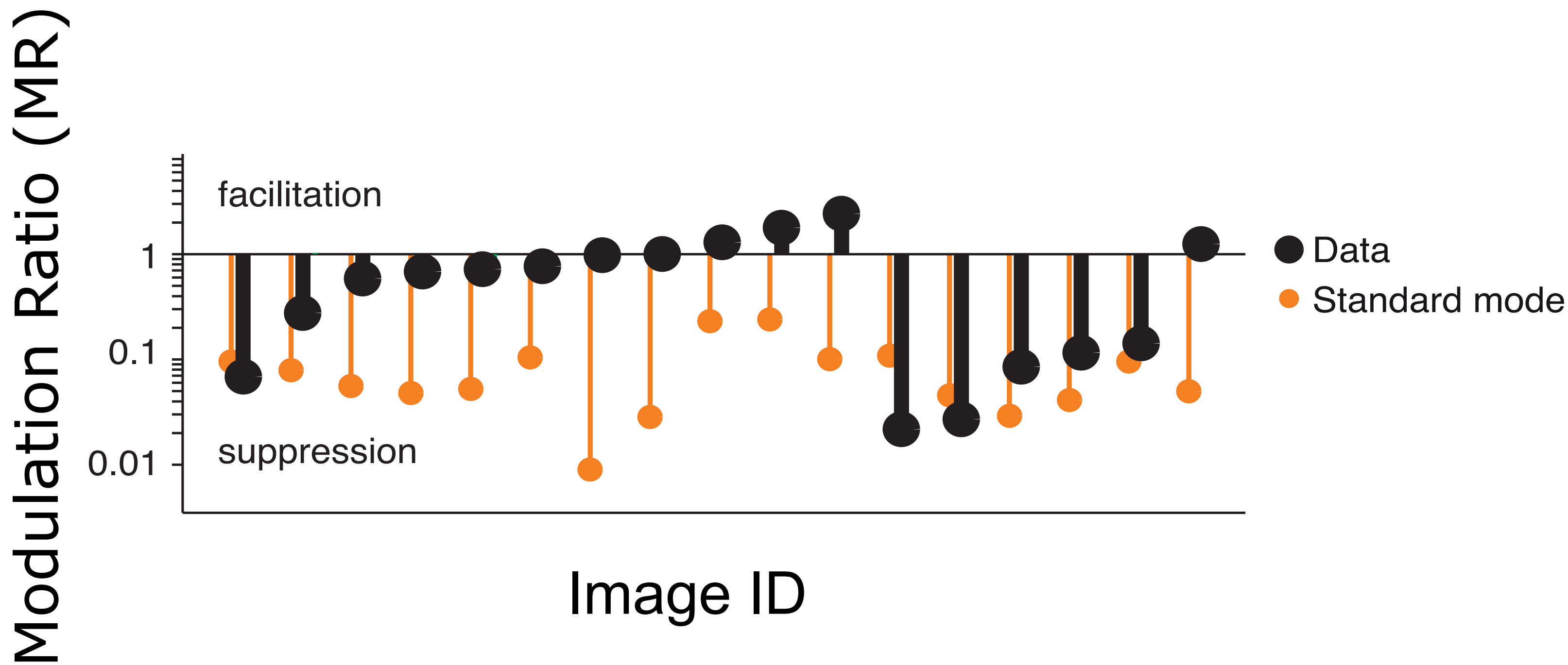


Canonical divisive normalization:

$$R_c \prec \frac{x_c}{\sqrt{x_c^2 + x_s^2}}$$

V1 Data: Kohn lab

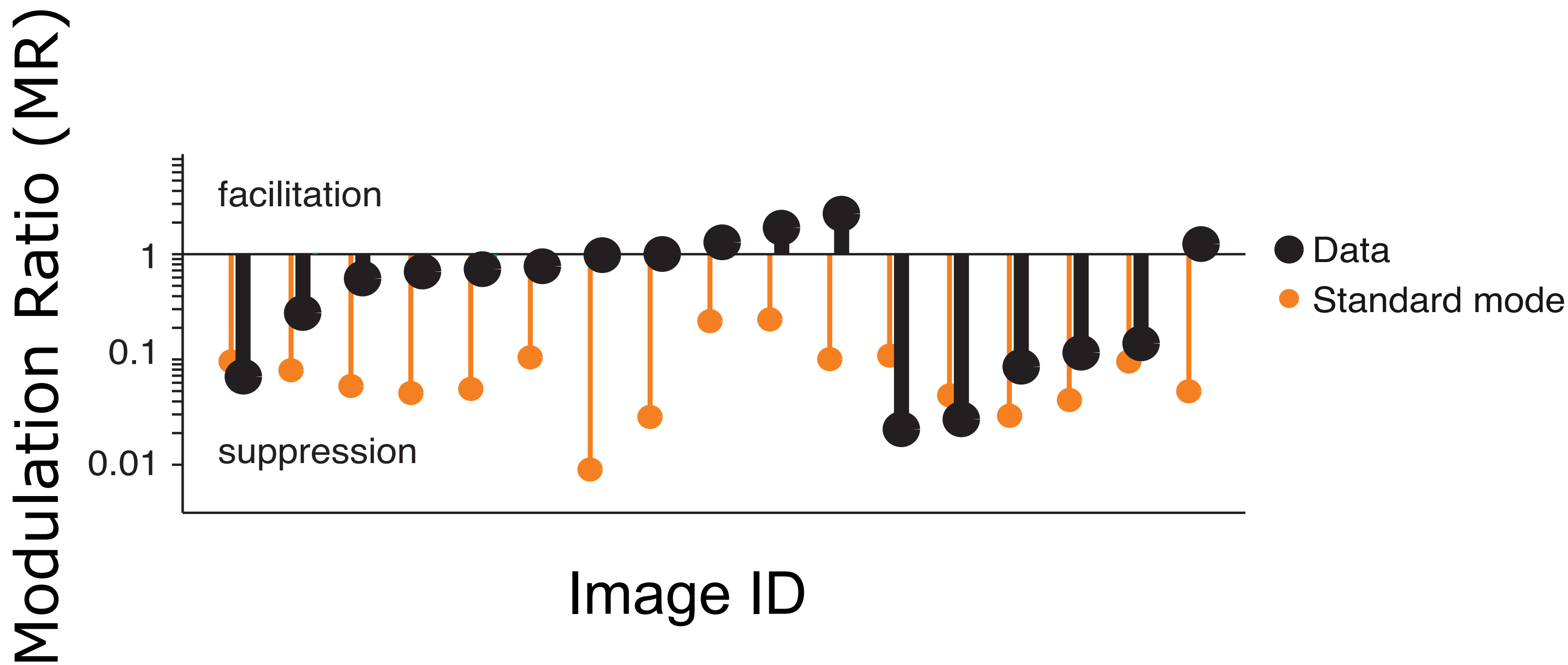
Cortical responses to natural images



- We fit the standard normalization model to neural data
- Poor prediction quality

Data: Adam Kohn lab
Coen-Cagli, Kohn, Schwartz, 2015 (in press)

Cortical responses to natural images



- Can we explain as strategy to encode natural images optimally based on expected contextual regularities?

Data: Adam Kohn lab
Coen-Cagli, Kohn, Schwartz, 2015 (in press)

Outline

- Experimental data on cortical responses to natural images (standard descriptive model can't explain)

- Computational neural model that captures contextual regularities in natural images

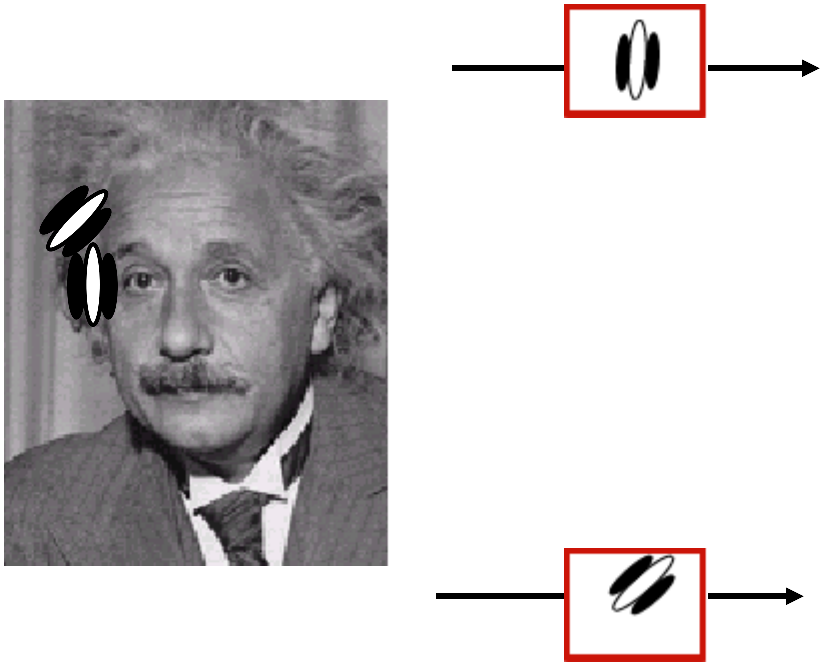
- A Interplay of modeling with biological neural and psychology data (focus on natural images data)

Two overarching computational principles

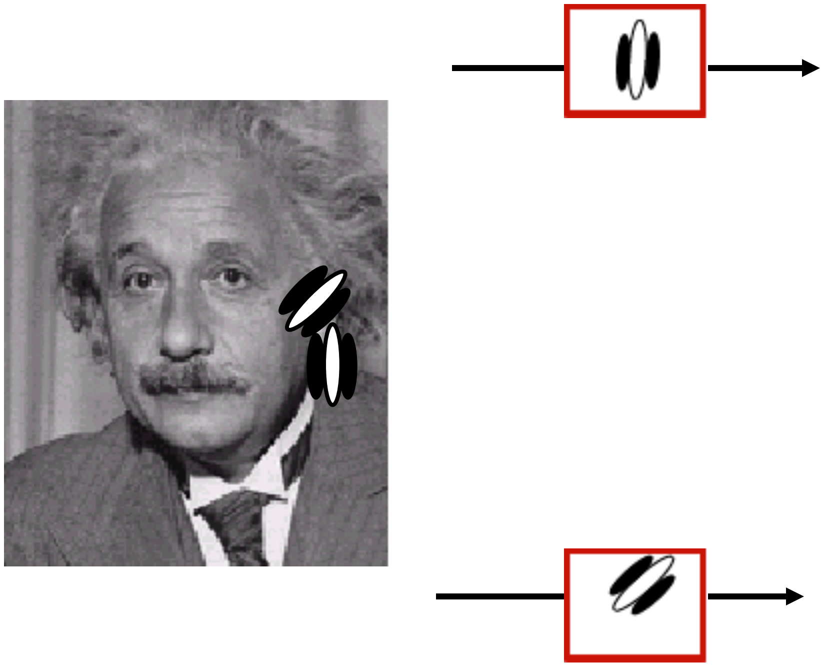
- Sensory processing as inference of properties of the input (can be formalized via probabilistic *Bayesian inference*)

- Sensory systems aim to form an *efficient code* by reducing redundancies of the input (Barlow; also Attneave); influenced by information theory in the 1950s

Contextual dependencies across space



Contextual dependencies across space



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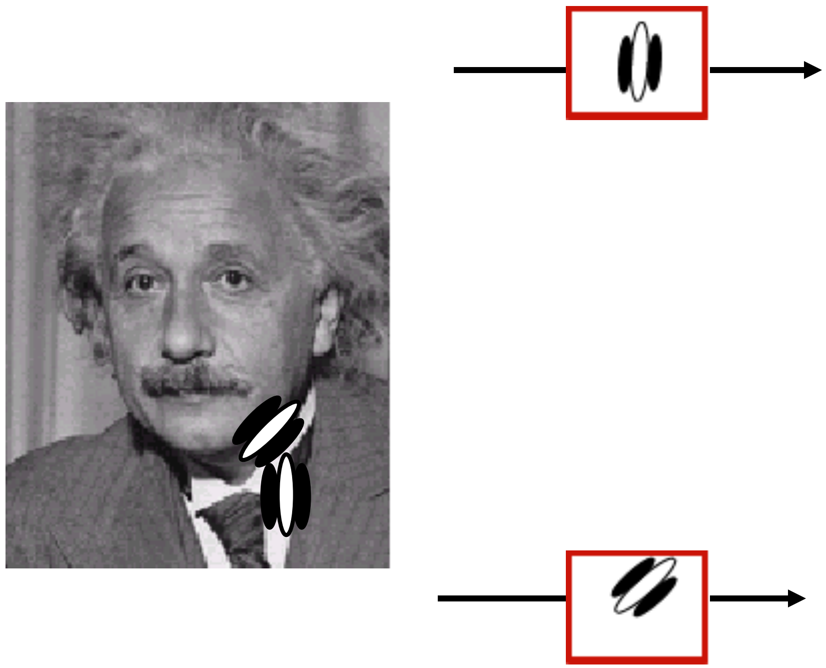
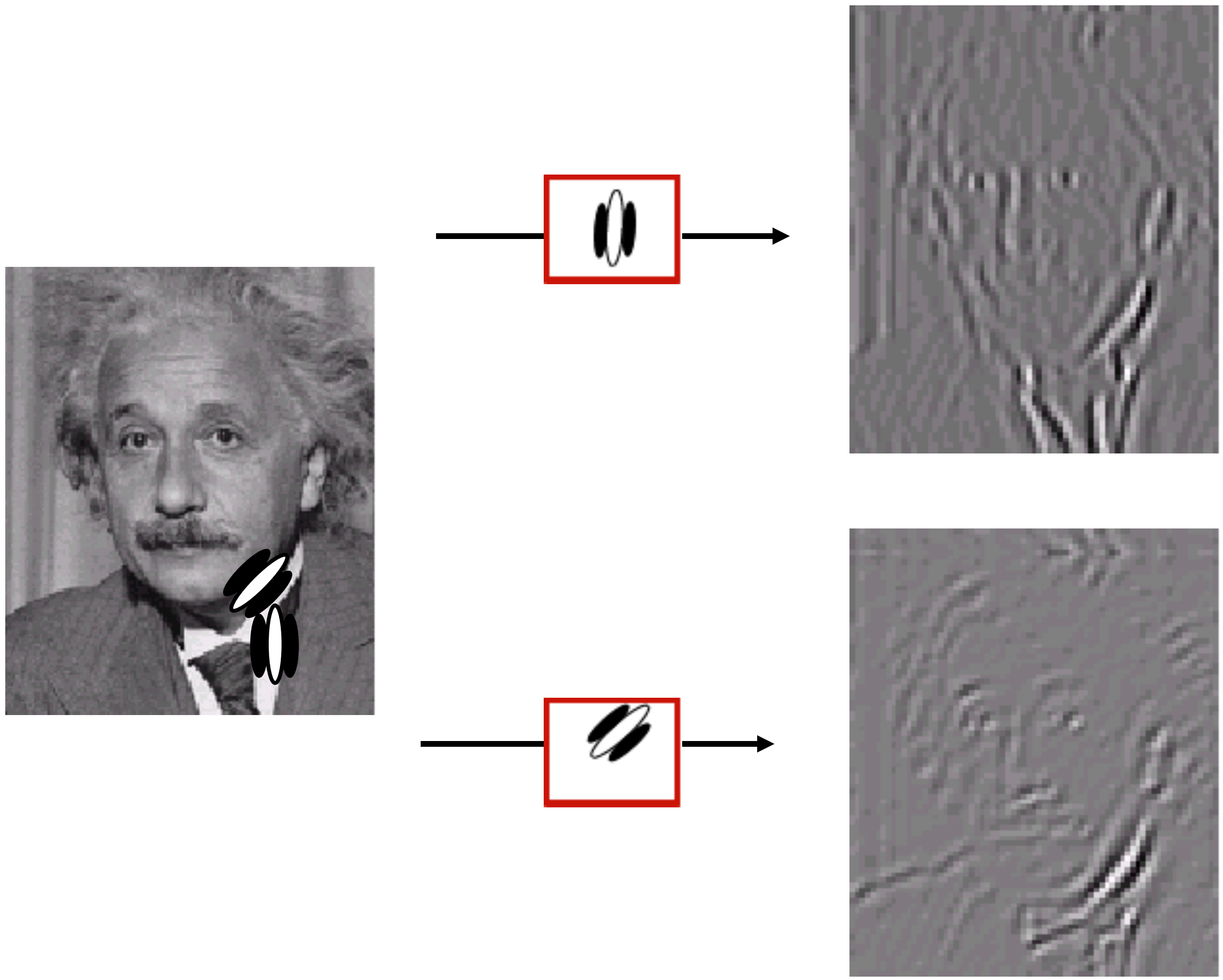
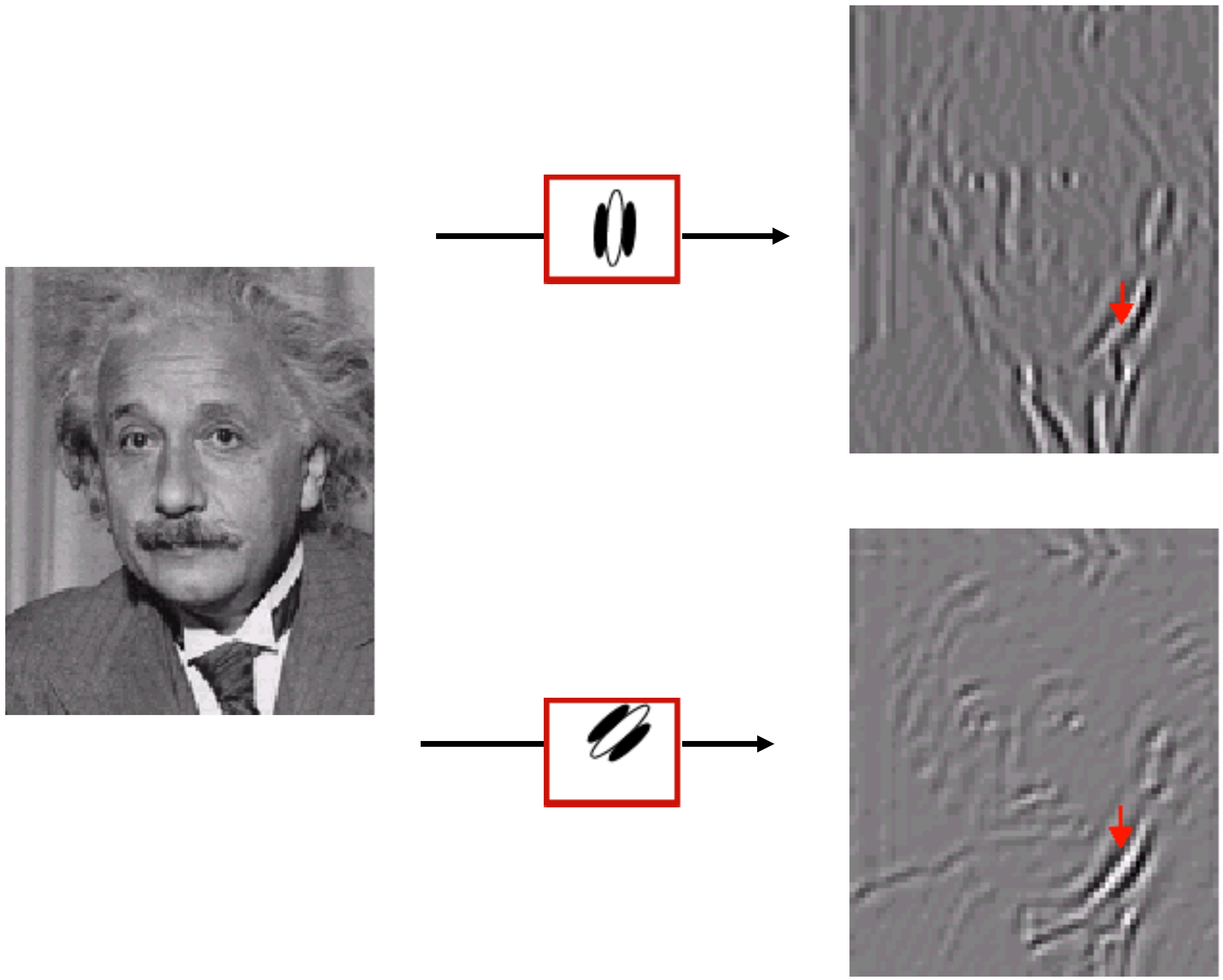


Contextual dependencies across space



Contextual dependencies across space



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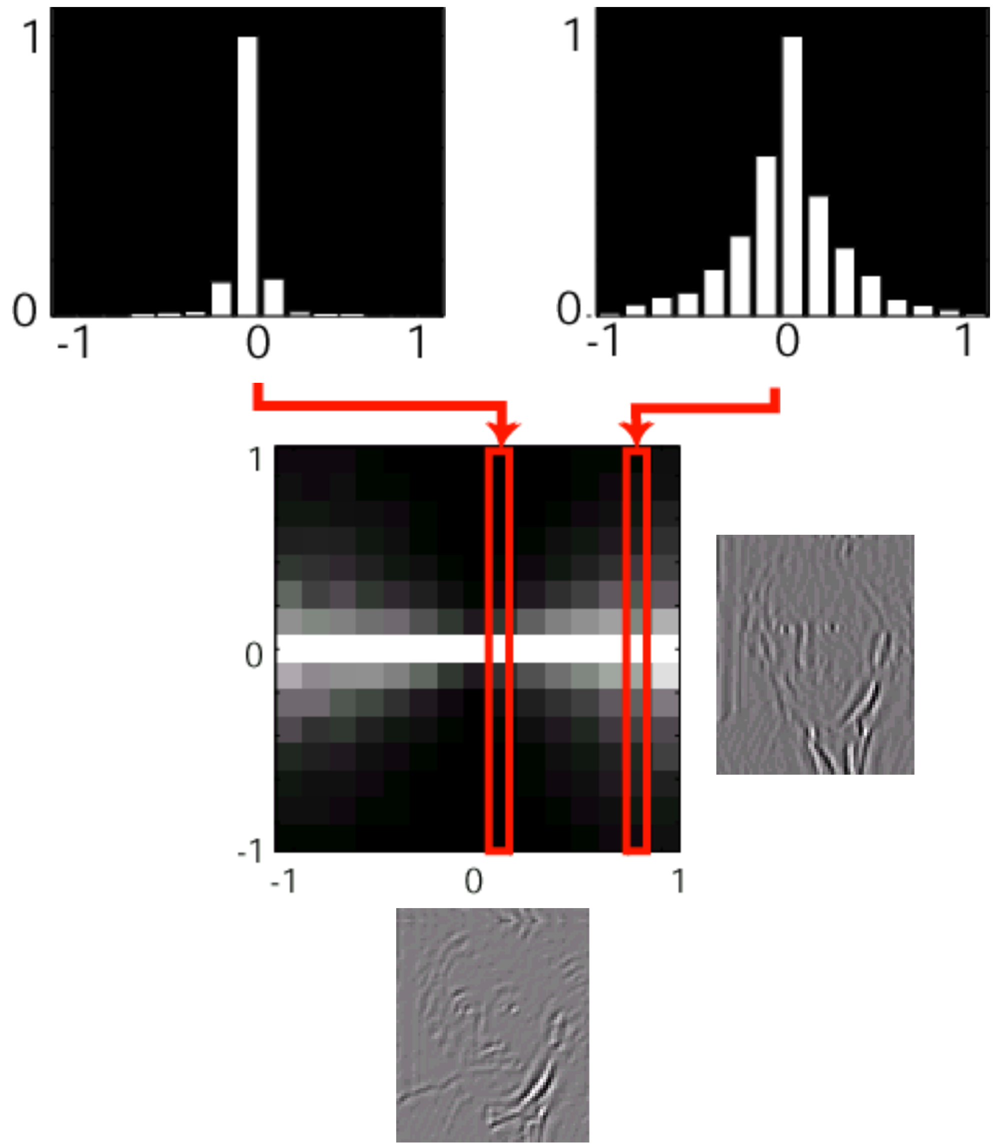
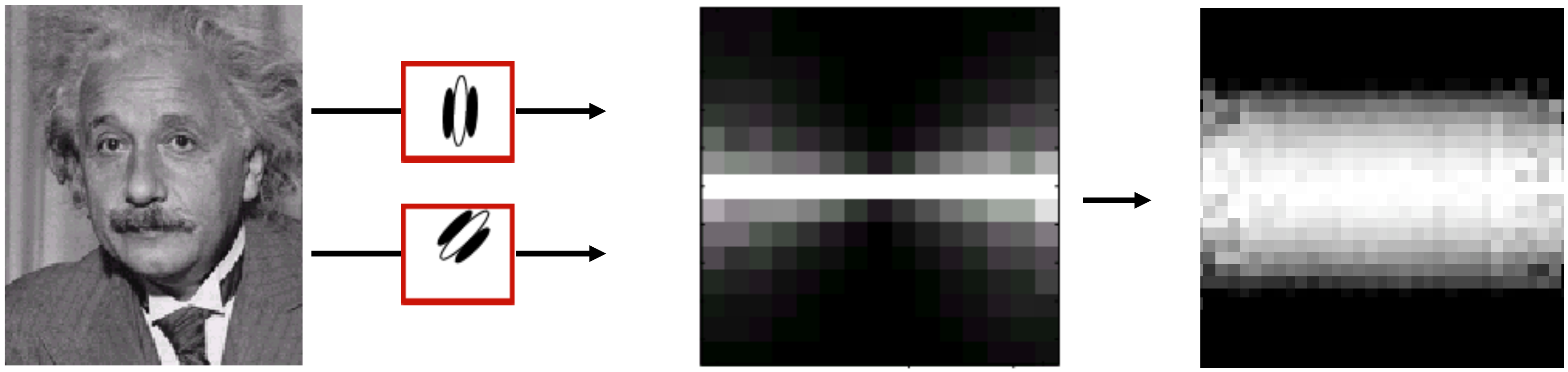


Schwartz, Simoncelli, Nature Neuroscience 2001

Generative model framework



- Hypothesize that cortical neurons aim to reduce statistical dependencies (so as to highlight what is salient)

  Schwartz, Simoncelli 2001 (for salience: Zhaoping Li, 2002)

- Formally, we build a generative model of the dependencies and invert the model (Bayesian inference) – richer representation!

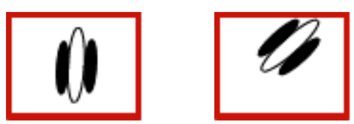
  Andrews, Mallows, 1974; Wainwright, Simoncelli, 2000; Schwartz, Sejnowski, Dayan 2006

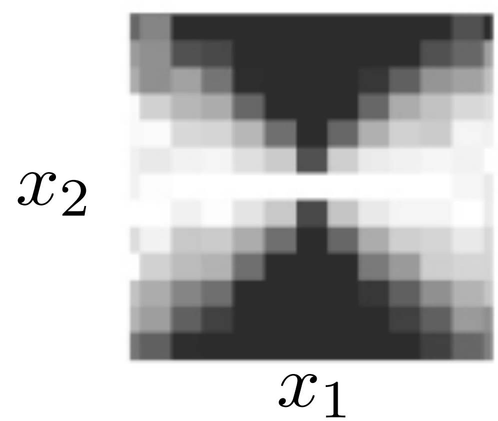
- Generating the dependencies is a multiplicative process and to undo the dependencies we divide

Modeling Statistical dependencies: Gaussian Scale Mixture (GSM)

x_1 x_2

Filter activations



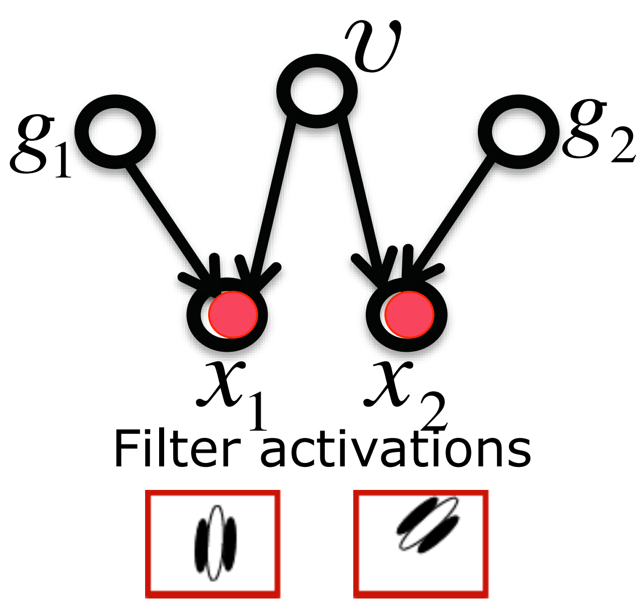


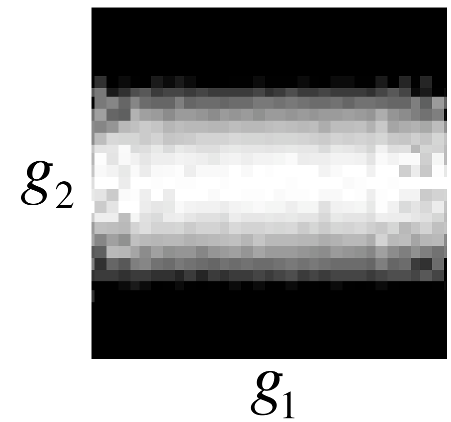
Andrews & Mallows, 1974; Wainwright & Simoncelli, 2000

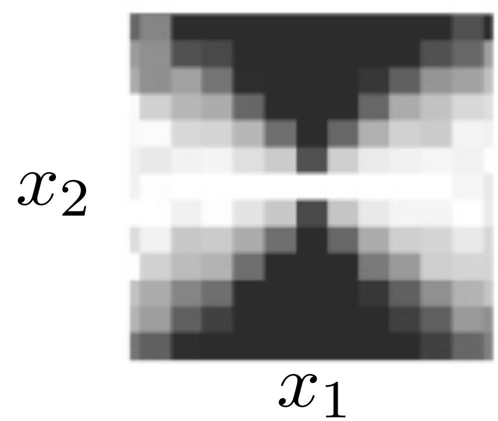
Modeling Statistical dependencies: Gaussian Scale Mixture (GSM)

Gaussians local
Global (shared) mixer

$$x_1 = v g_1$$
$$x_2 = v g_2$$







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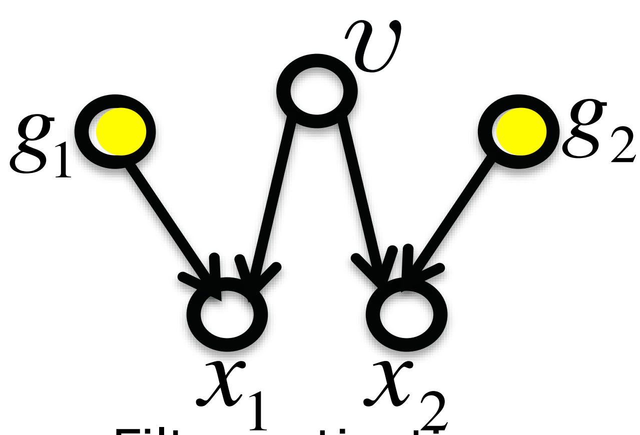
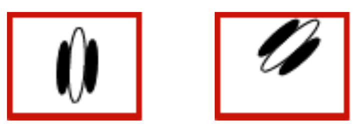


Infer local Gaussian

Filter activations

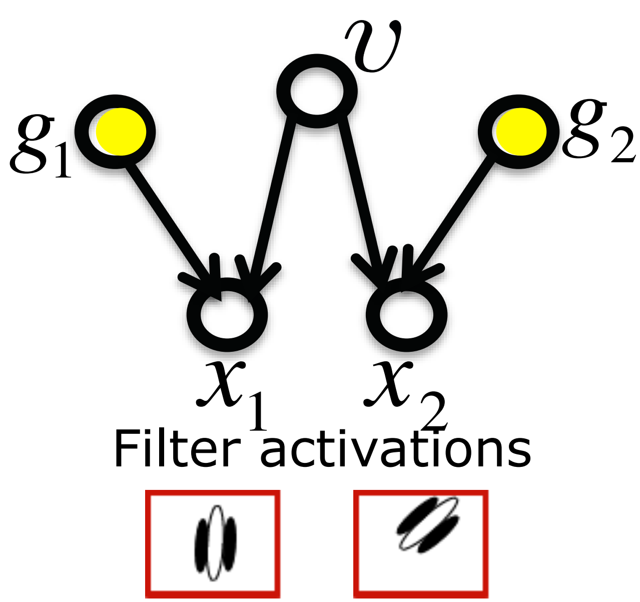


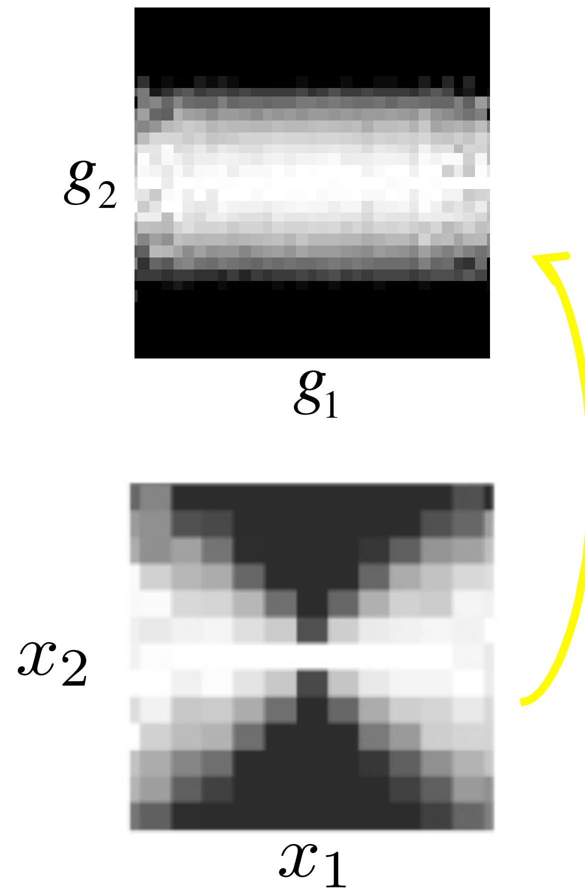
$E(g_1 \mid x_1, x_2) =$ Model neuron activity

Modeling Statistical dependencies: Gaussian Scale Mixture (GSM)

$$x_1 = v g_1$$
$$x_2 = v g_2$$

Gaussians local
Global (shared) mixer

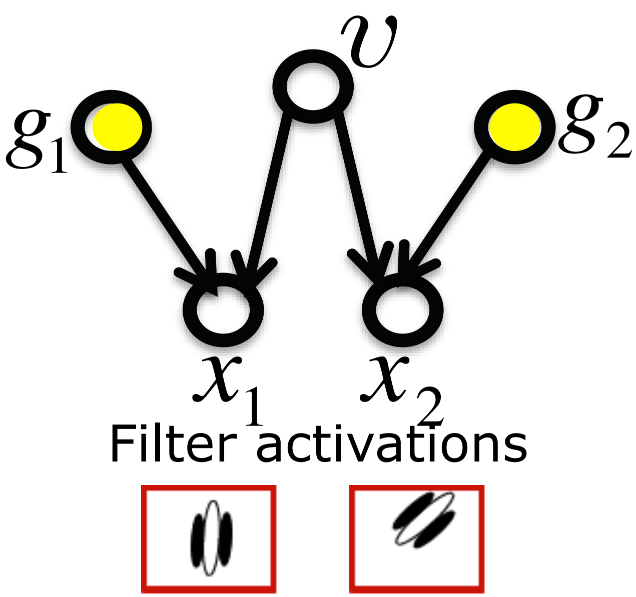




EFFICIENT CODING

Modeling Statistical dependencies: Gaussian Scale Mixture (GSM)

Gaussians local
Global (shared) mixer



Computed via Bayes rule

$$E(g_1 \mid x_1, x_2) \prec \boxed{\frac{x_1}{\sqrt{l}}};$$

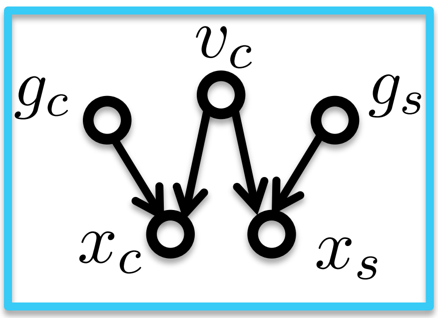
$$l = \sqrt{x_1^2 + x_2^2}$$

DIVISIVE
NORMALIZATION

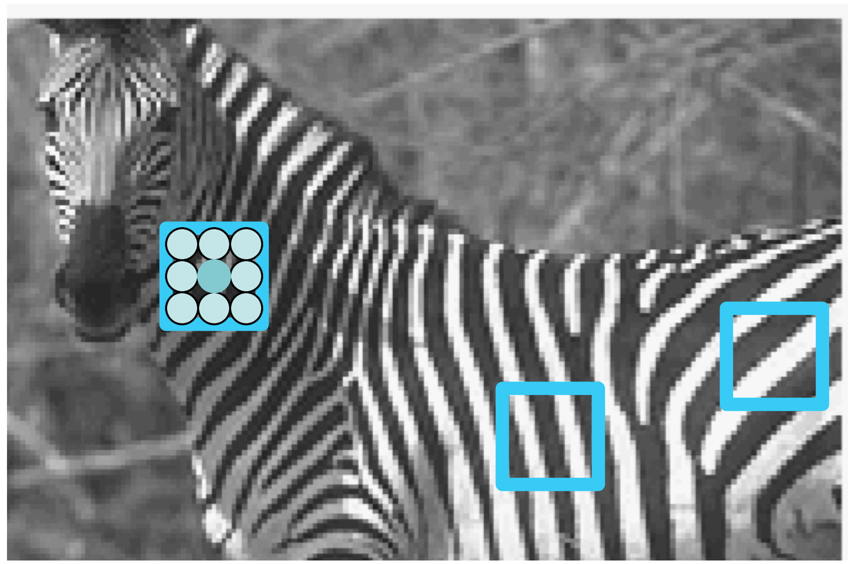
Divisive Normalization Canonical Model

Divisive normalization *descriptive* models have been applied in many neural systems. Here we provide a *principled explanation.* We will next show that it also leads to a richer model based on image statistics and makes predictions

Non-homogeneity of images



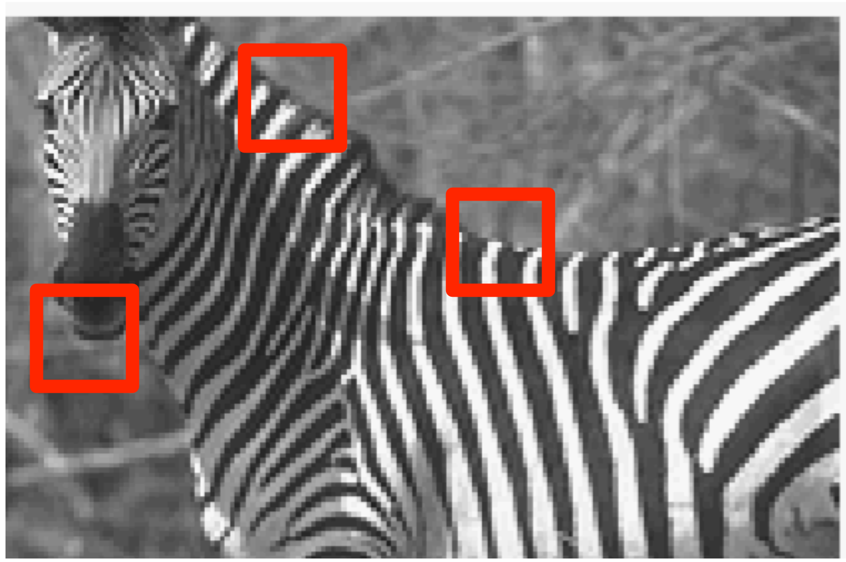
Center and surround
dependent



homogenous image patches

Schwartz, Sejnowski, Dayan, 2009; Coen-Cagli, Dayan, Schwartz, PLoS Comp Biology 2012

Non-homogeneity of images



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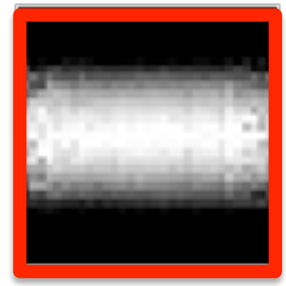

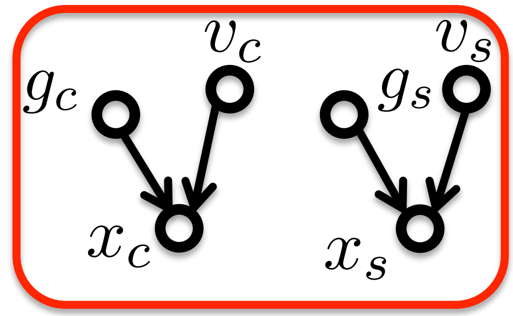

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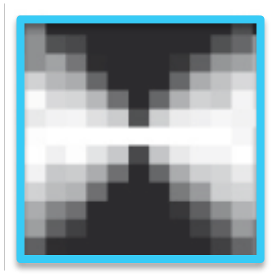
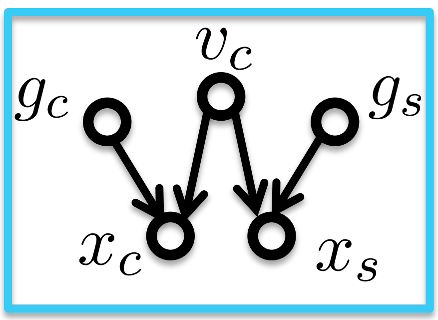
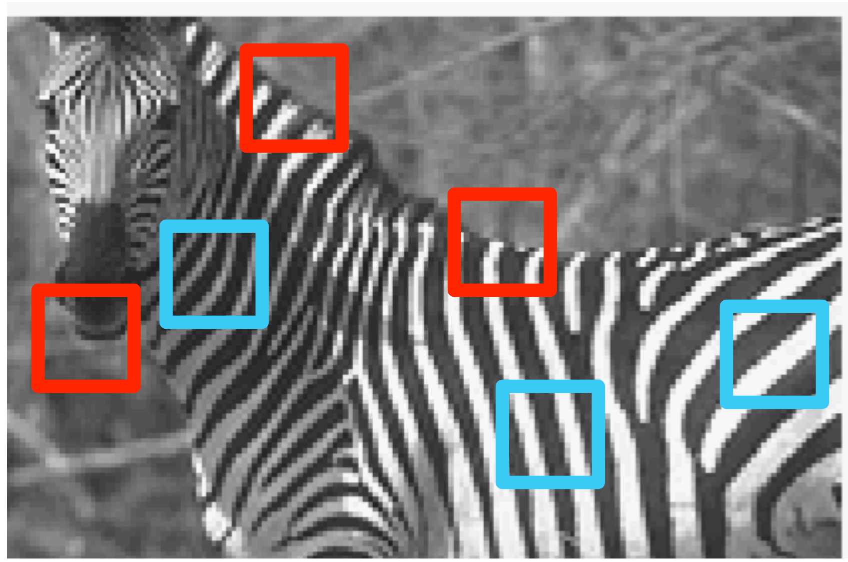
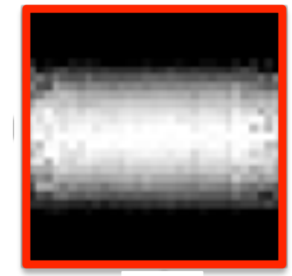
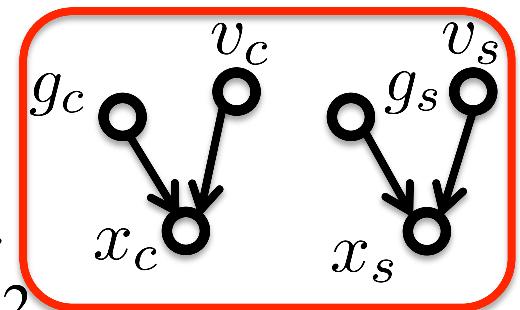




ξ_1







ξ_2

divisive normalization ON

divisive normalization OFF

$$E[g_c \mid x_c, x_s] = p(\xi_1 \mid x_c, x_s) E[g_c \mid x_c, x_s, \xi_1] + p(\xi_2 \mid x_c, x_s) E[g_c \mid x_c, \xi_2]$$

Schwartz, Sejnowski, Dayan, 2009; Coen-Cagli, Dayan, Schwartz, PLoS Comp Biology 2012

Non-homogeneity of images

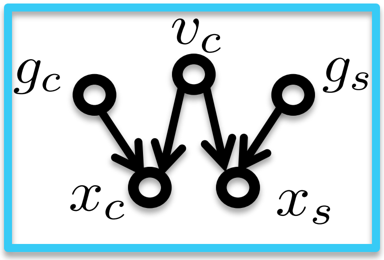
$$E[g_c \mid x_c, x_s] = p(\xi_1 \mid x_c, x_s) E[g_c \mid x_c, x_s, \xi_1] + p(\xi_2 \mid x_c, x_s) E[g_c \mid x_c, \xi_2]$$

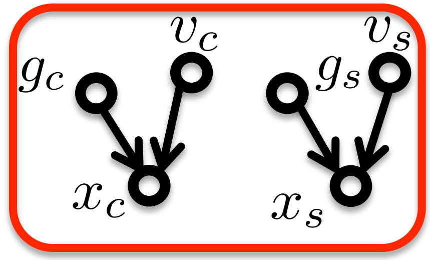
$$p(\xi_1 \mid x) \prec p(\xi_1) p(x \mid \xi_1) = p(\xi_1) \int dv_c \, p(v_c) p(x \mid v_c, \xi_1);$$

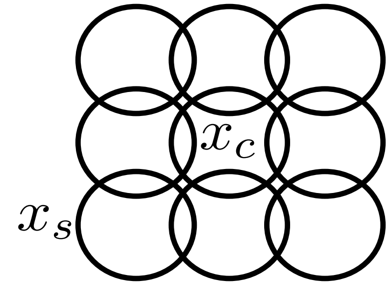
$$p(\xi_2 \mid x) \prec p(\xi_2) p(x \mid \xi_2) = p(\xi_2) \int dv_c \, p(v_c) p(x_c \mid v_c, \xi_2) \int dv_s \, p(v_s) p(x_s \mid v_c, \xi_2)$$

Schwartz, Sejnowski, Dayan, 2009; Coen-Cagli, Dayan, Schwartz, PLoS Comp Biology 2012

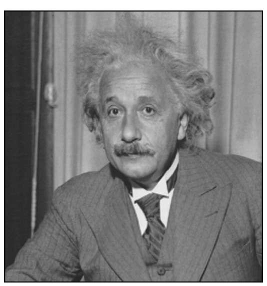
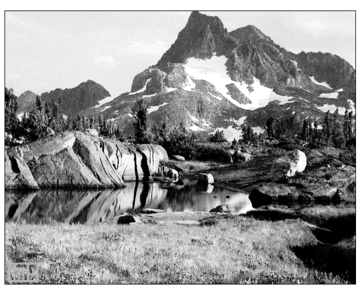
Model: Optimizing Image Ensemble







- 3x3 spatial positions, 6px separation
- 4 orientations in the center
- 4 orientations in the surround
- 2 phases (quadrature)
- model parameters (prior probability for ξ_1, ξ_2 and also linear covariance matrices) optimized to maximize the likelihood of a database of natural images using Expectation Maximization

Coen-Cagli, Dayan, Schwartz, PLoS Comp Biology 2012;
Schwartz, Sejnowski, Dayan, 2006

Outline

- Experimental data on cortical responses to natural images
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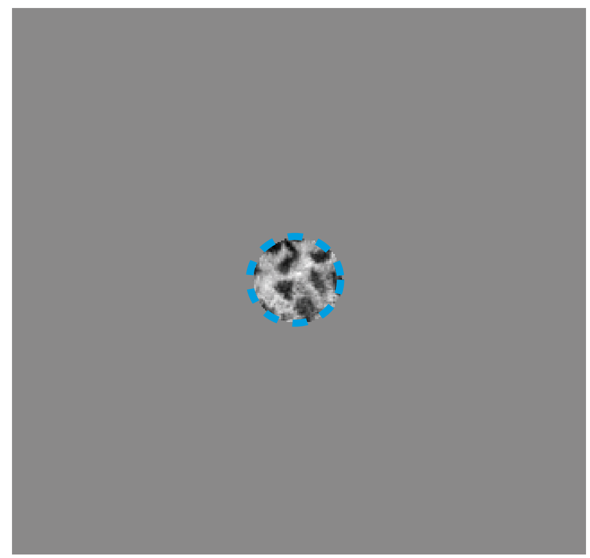
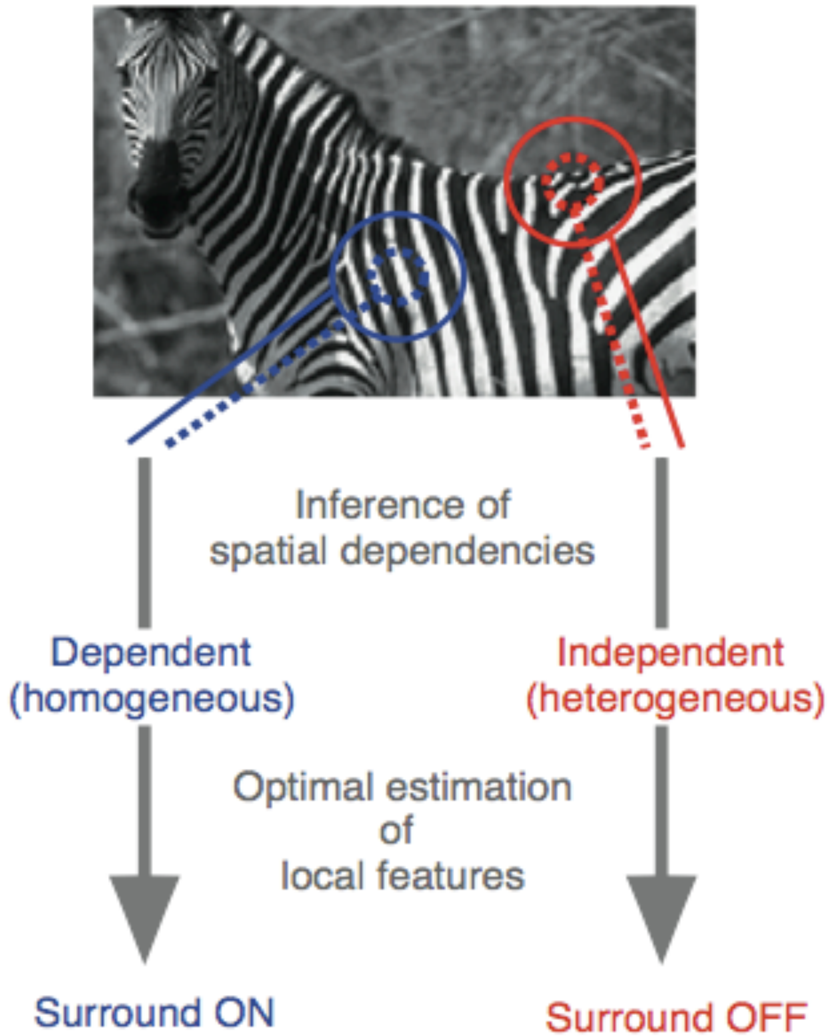
Cortical predictions for natural images

- In the past, we have tested modeling with simple stimuli
  (e.g., Coen-Cagli, Dayan, Schwartz, 2012; Schwartz, Sejnowski, Dayan, 2009)

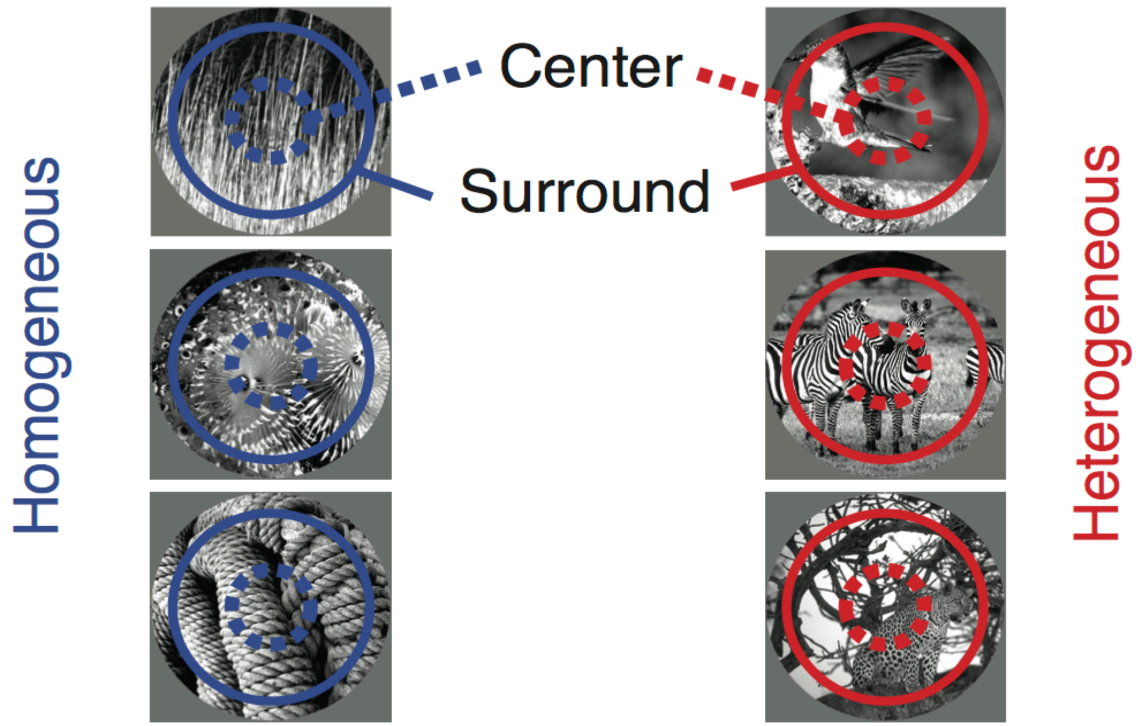
- Here, we make predictions for natural images
  (Coen-Cagli, Kohn, Schwartz, 2015, in press)



Flexible Divisive Normalization



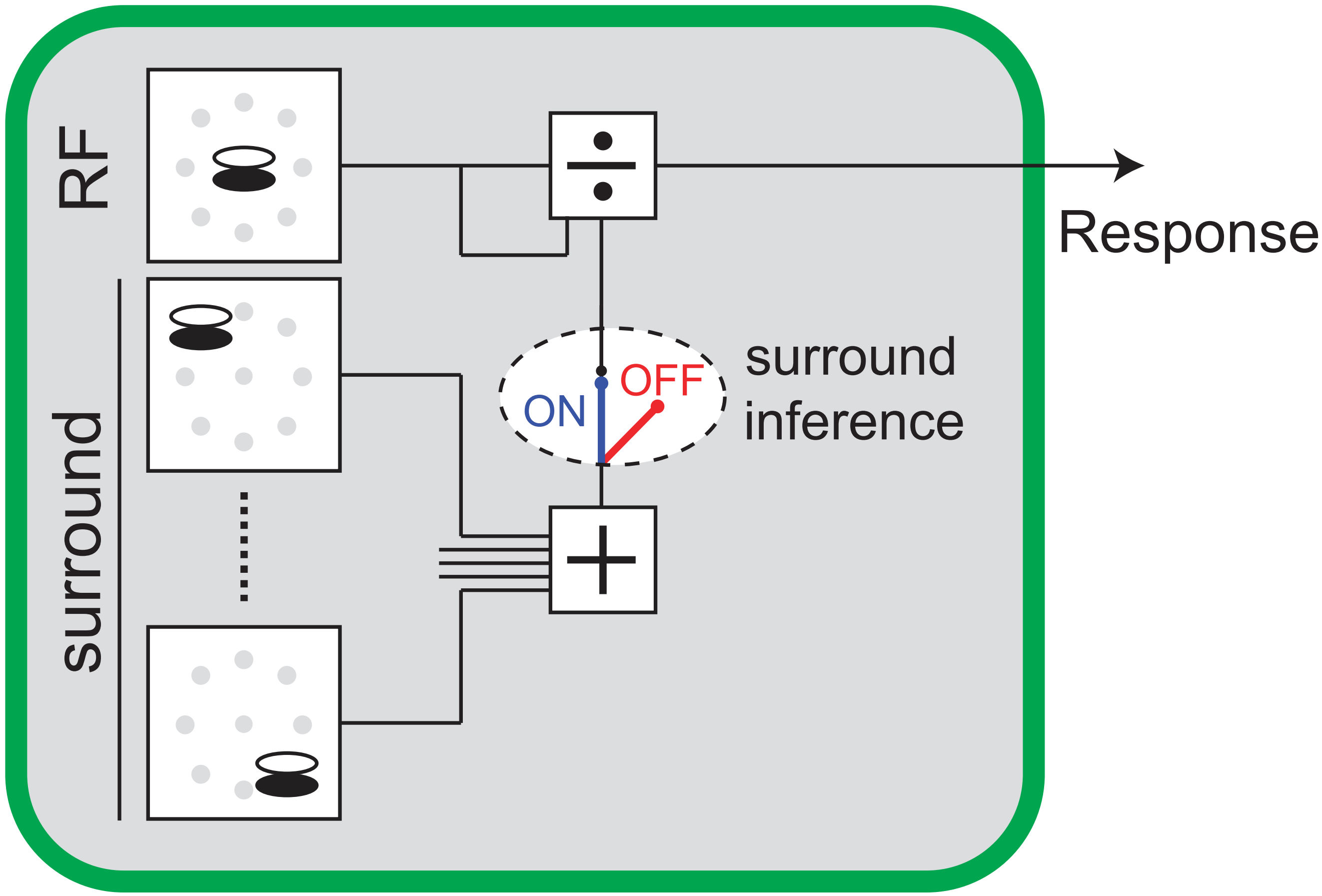
Model predictions for natural images



- **Homogeneous and heterogeneous determined by model!**
- Expect more suppression in neurons for homogeneous
- Related to salience (eg, Zhaoping)

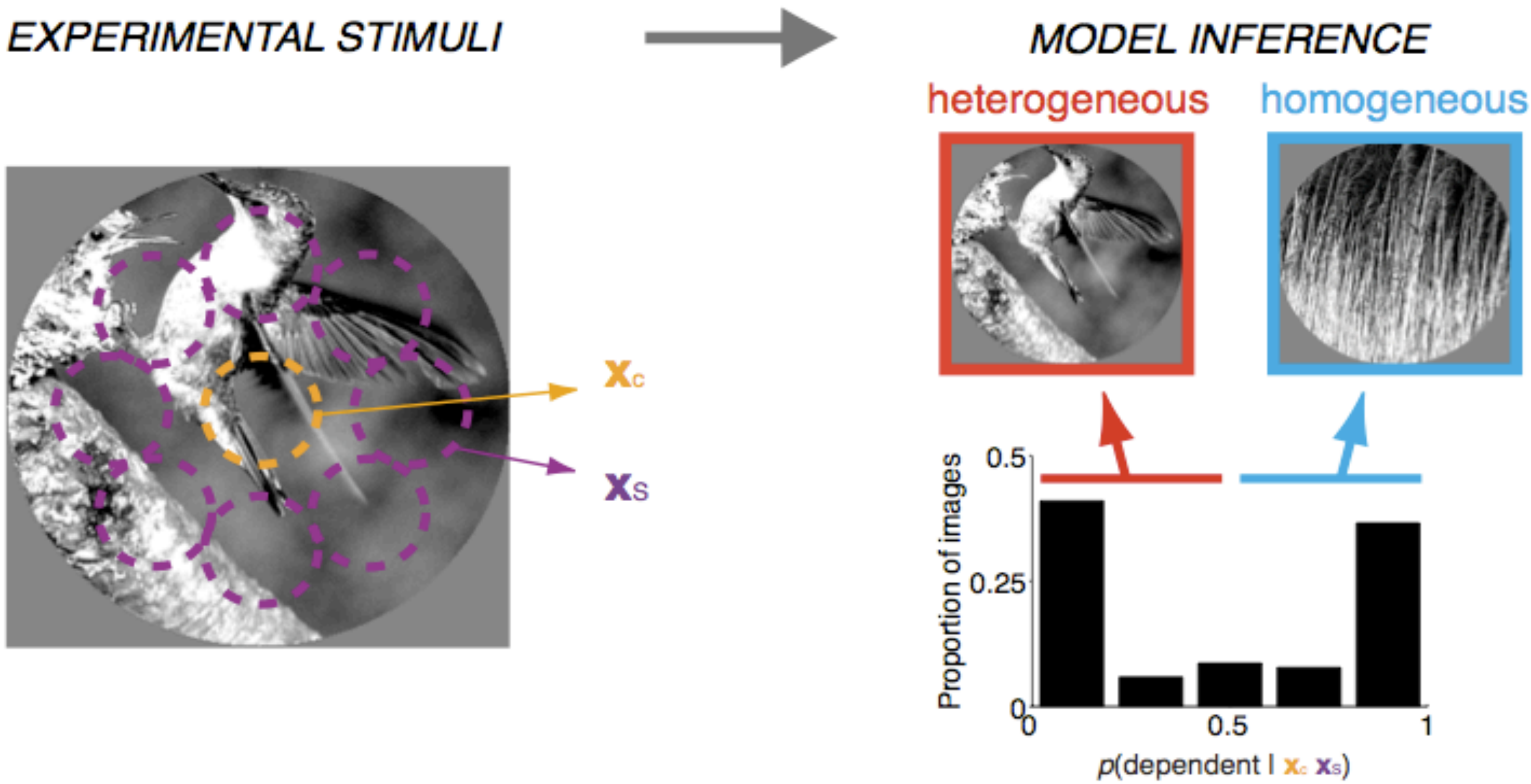
Coen-Cagli, Kohn, Schwartz, 2015; in press

Model summary



Inference determined by model

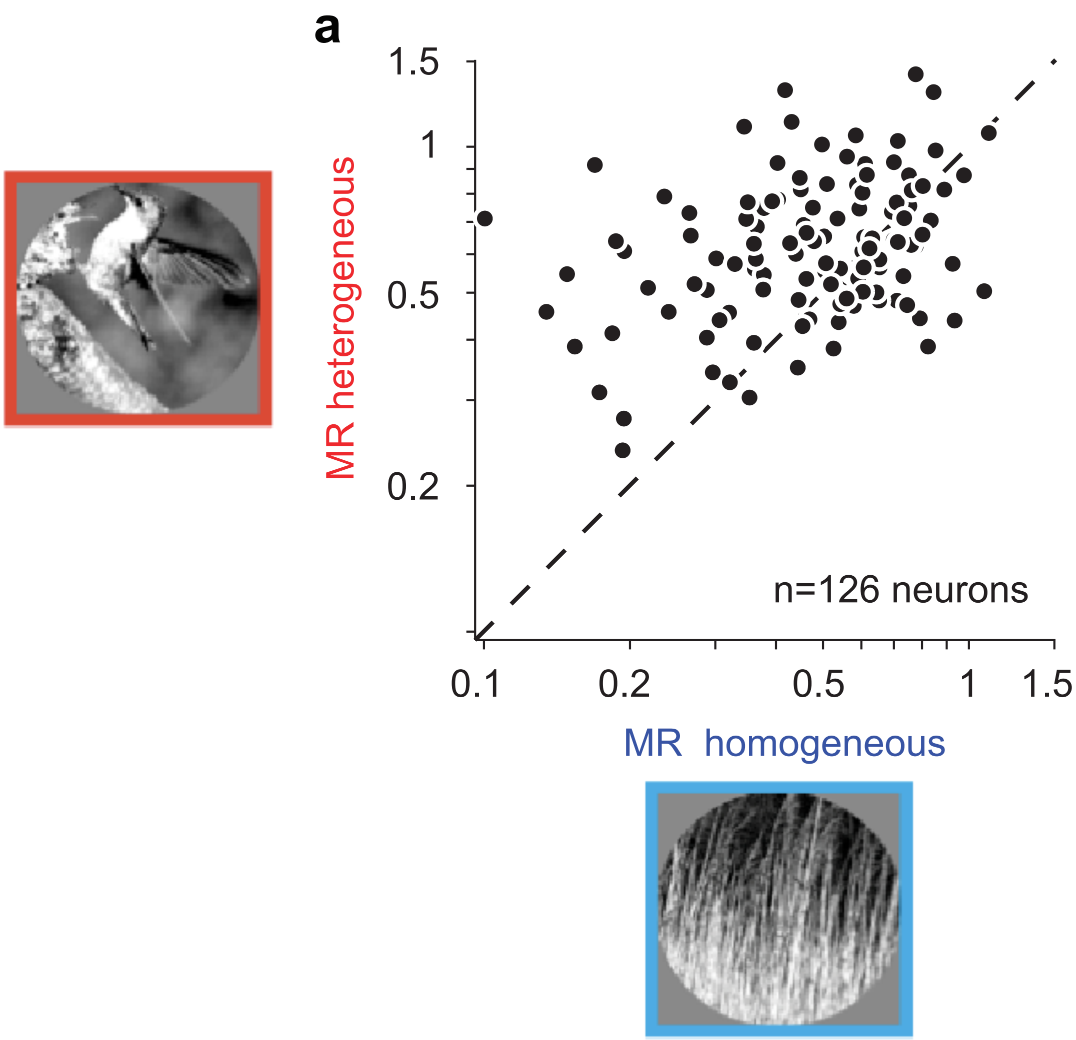
Model Predictions for Natural Scenes



homogeneous versus heterogeneous determined by the model

Model Predictions for Natural Scenes

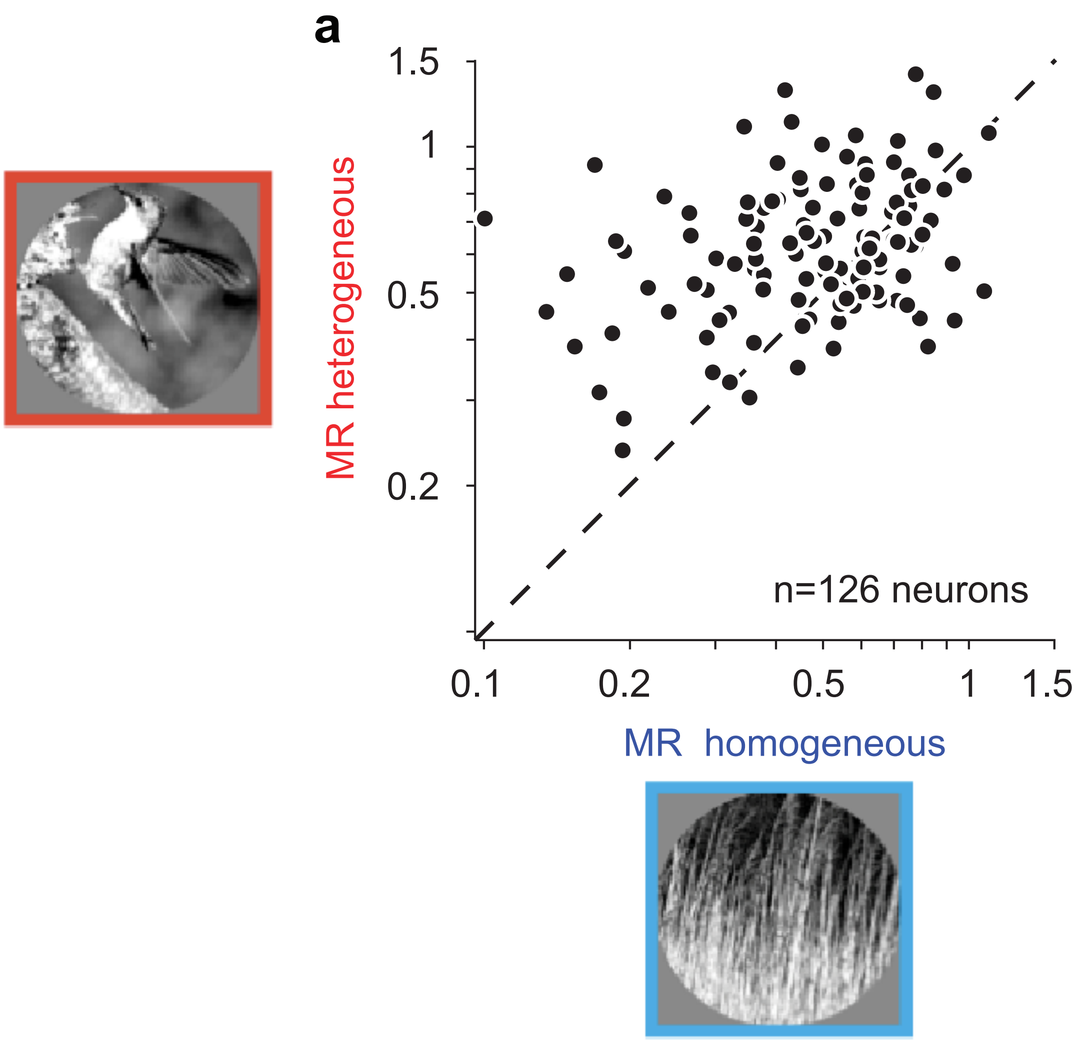
Cortical V1 data:



Coen-Cagli, Kohn, Schwartz, 2015, in press

Model Predictions for Natural Scenes

Cortical V1 data:

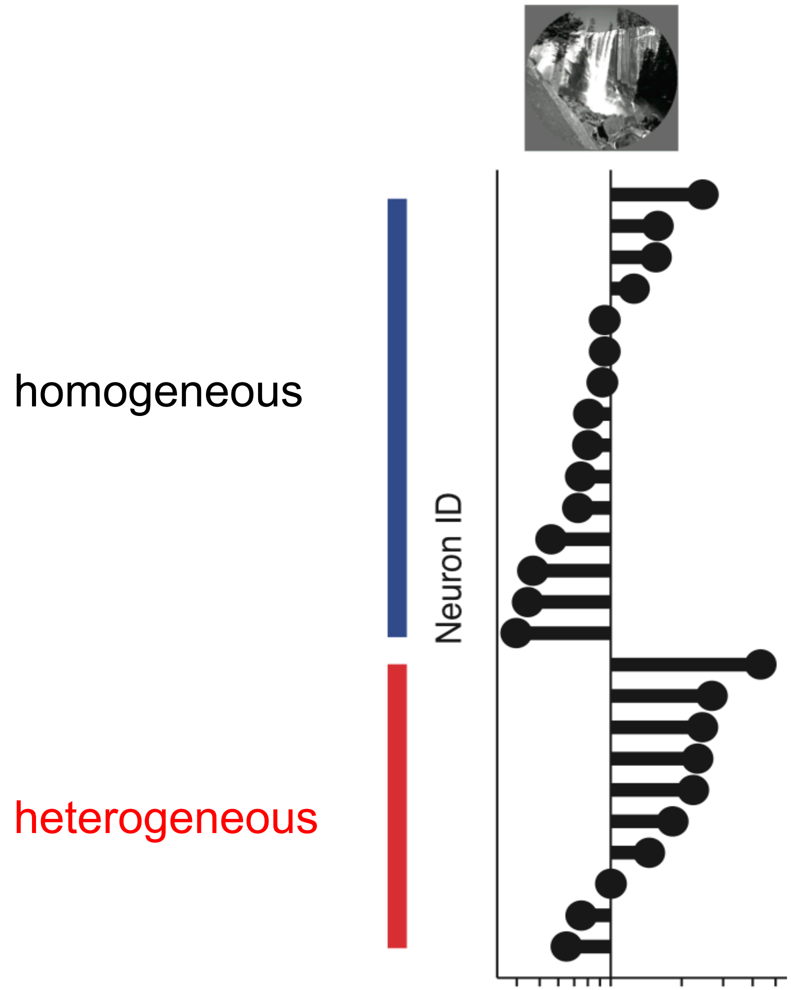


Not explained by:
- firing rate with small frames
- surround energy

Coen-Cagli, Kohn, Schwartz, 2015, in press

Model predictions for natural images

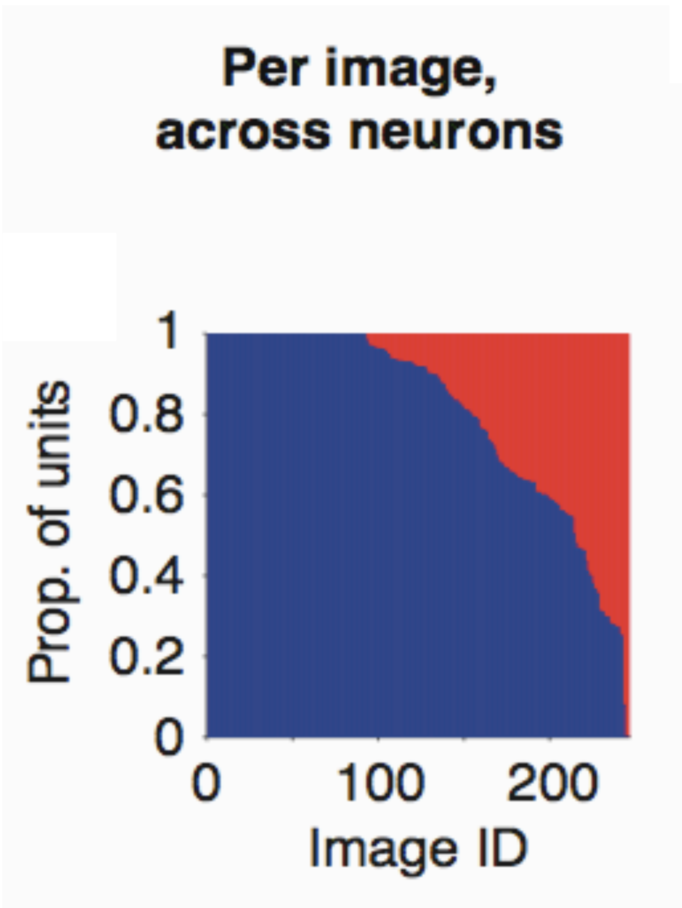
- Per image, across neurons

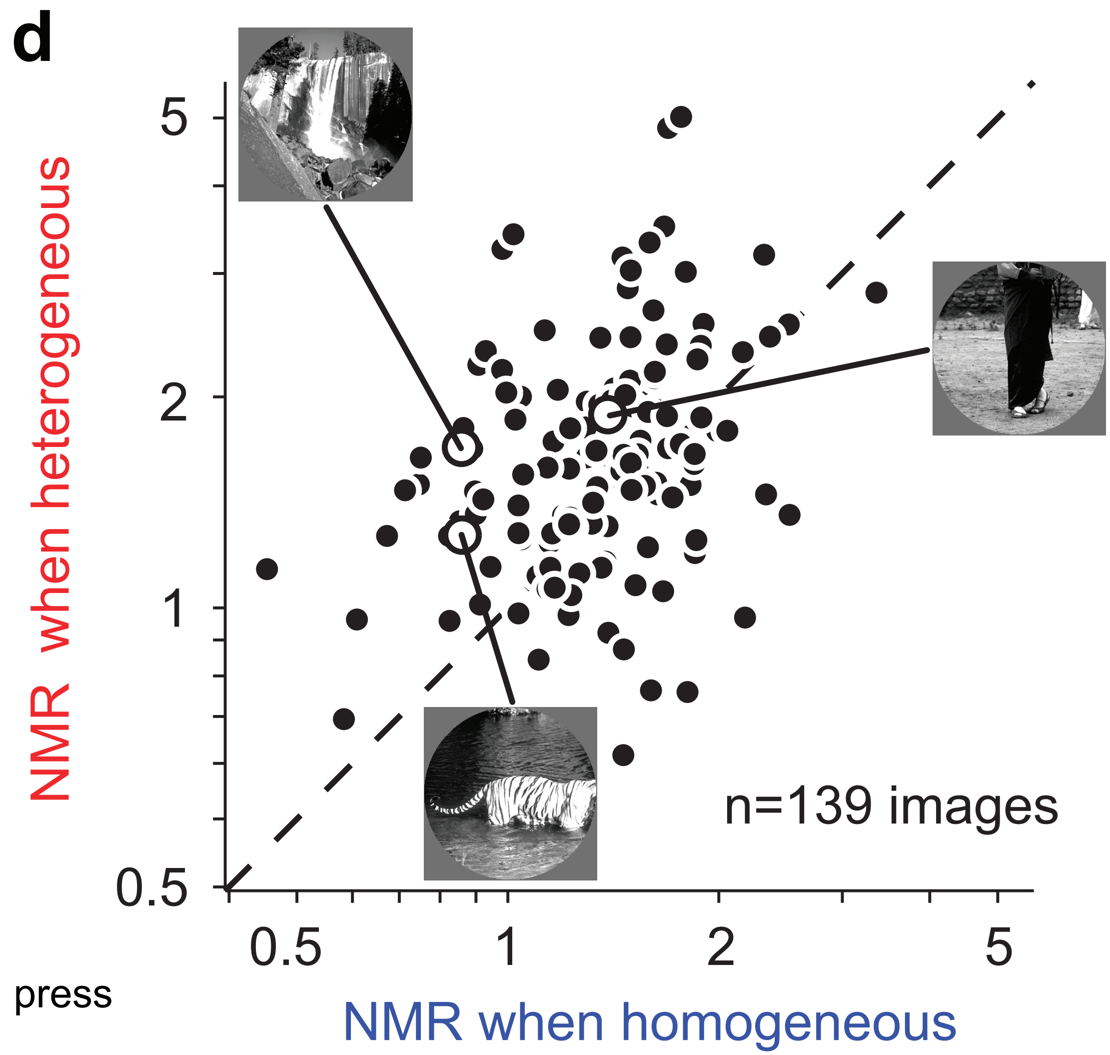


Coen-Cagli, Kohn, Schwartz, 2015; in press

Model predictions for natural images

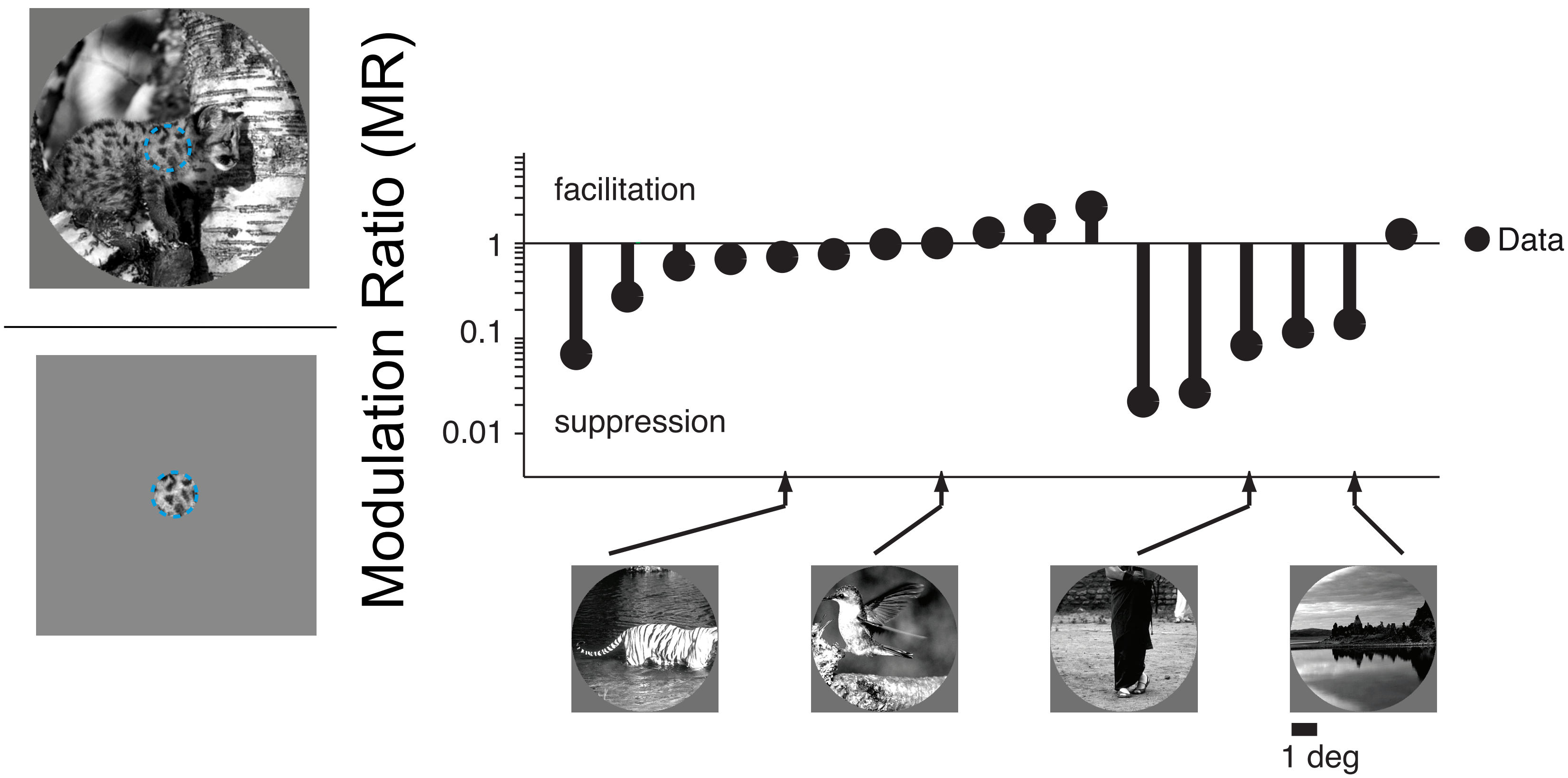
- Testing predictions with cortical data





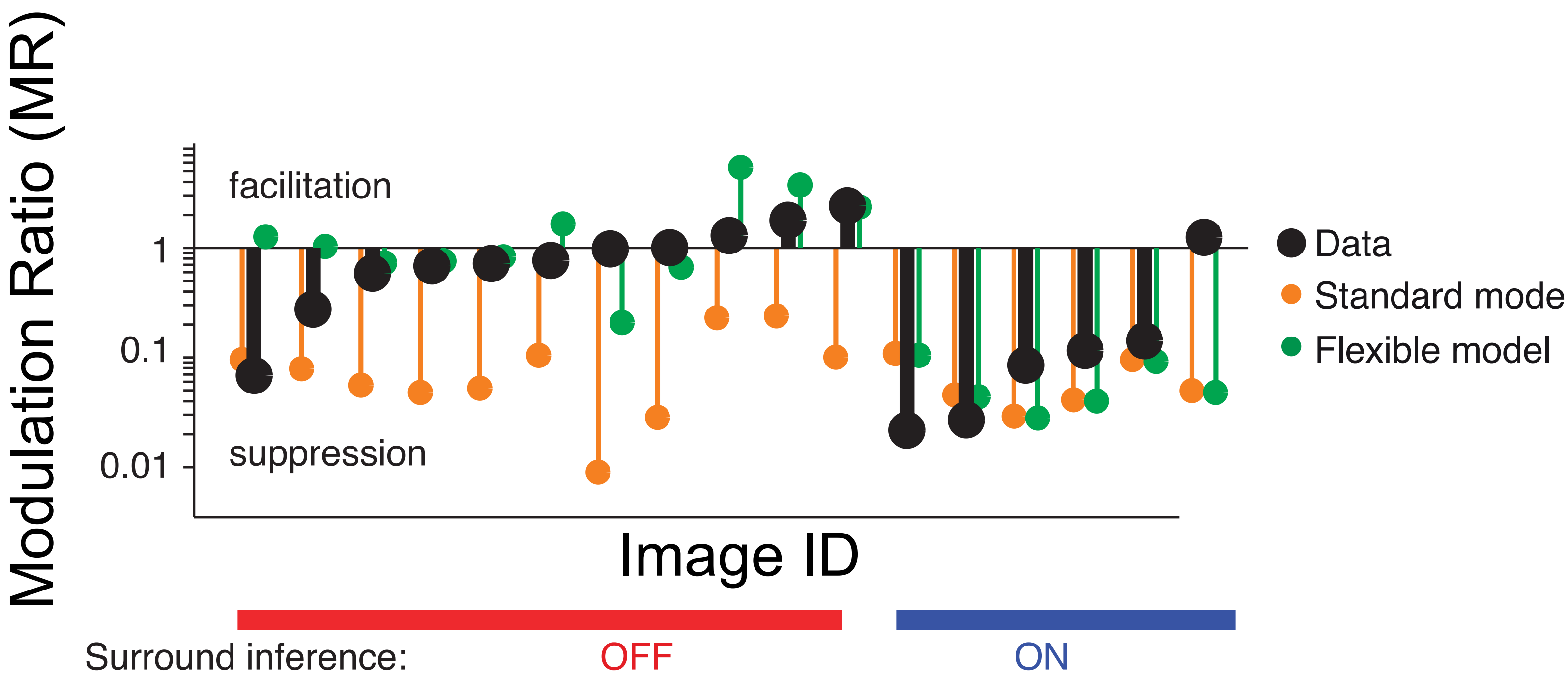
Coen-Cagli, Kohn, Schwartz, 2015; in press

Natural scenes data



Coen-Cagli, Kohn, Schwartz, 2015, in press

Natural scenes data



Coen-Cagli, Kohn, Schwartz, 2015, in press

Model predictions for natural images

- Comparing model performance for cortical data

Standard divisive normalization

$$R_i = \alpha\left(\frac{E_{c,\phi_{pref}}}{\varepsilon + \beta E_c + \gamma E_s}\right)^n$$

Flexible divisive normalization:

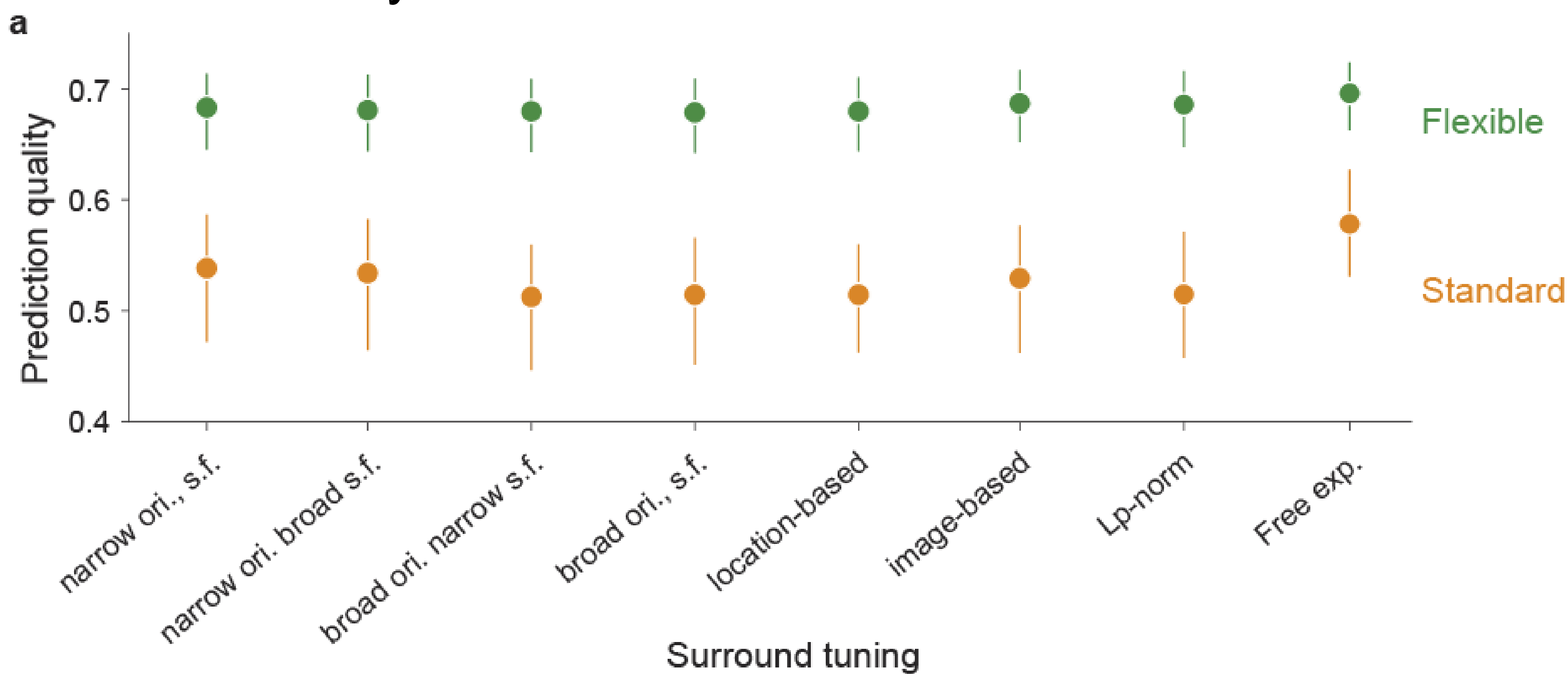
$$R_i = \alpha\left(\frac{E_{c,\phi_{pref}}}{\varepsilon + \beta E_c + \boxed{q(c,s)}\gamma E_s}\right)^n$$

Determined by the model (not fit!)
1 if $p(\xi_1 \mid c,s) \geq 0.5$
0 otherwise

(similar results if non binary)

Natural scenes data

- Cross-validated prediction quality
- There are many standard model versions…



Prediction quality:
- 1 = “oracle” (observed mean for each image)
- 0 = “null” (mean response across all images)

Coen-Cagli, Kohn, Schwartz, 2015, in press

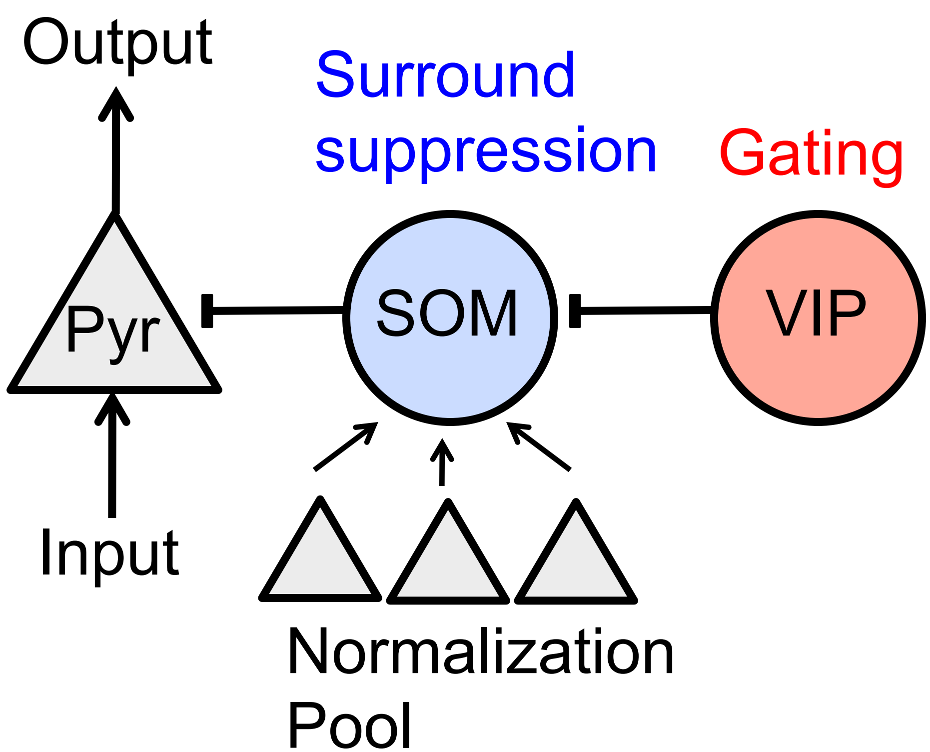
Model Mechanisms

Divisive normalization:

- Feedback inhibition
- Distal dendrite inhibition
- Depressing synapses
- Internal biochemical adjustments
- Non-Poisson spike generation

Flexible Normalization Mechanism?

- Adjusting gain by circuit or postsynaptic mechanisms?
- Distinct classes of inhibitory interneurons? (eg, Adesnik, Scanziani et al. 2012; Pfeffer, Scanziani et al. 2013; Pi, Kepecs et al. 2013; Lee, Rudy et al. 2013)



Key take-home points

- New approach to understanding cortical processing of natural images. Rather than fitting more complicated models, use insights from scene statistics

- Connects to neural computations that are ubiquitous, but enriches the “standard” model

- Our results suggest flexibility of contextual influences in natural vision, depending on whether center and surround are deemed statistically homogeneous

- Next/currently: hierarchical representations; adaptation

Acknowledgments

Albert Einstein
Ruben Coen Cagli
Adam Kohn

Gatsby, UCL
Peter Dayan

Salk Institute
Terry Sejnowski

Funding
NIH (Collaborative Research in Computational Neuroscience)
Army Research Office
Alfred P. Sloan Foundation
Google